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FROM PARTNER SELECTION TO COLLABORATION IN INFORMATION SHARING MULTI-AGENT SYSTEMS

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FROM PARTNER SELECTION TO COLLABORATION IN INFORMATION SHARING MULTI-AGENT SYSTEMS

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Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

The University of Texas at Austin

August 2006

Dedication

This dissertation is dedicated to my wife Soyoung Kim,

my daughters Sophia J. Park and Chloe J. Park,

and my parents Hang-gu Park and Kyunghee Kim

Acknowledgements

I would like to thank all the people who helped me through the entire process of completing my dissertation. I begin with my parents, Hang-gu Park and Kyunghee Kim, who have always been supportive on what I have been done. My wife Soyoung Kim, and my daughters Sophia Joowon Park, Chloe Joohee Park have also been the biggest support for me. My supervisor Dr. K. Suzanne Barber has been a constant and prominent pedestal for my research and has encouraged me in my times of need. Next are the administrative staffs for the LIPS lab, Charlotte and Darla, and my current labmates, David Han, Karen Fullam, Jaesuk Ahn, Nishit Gujral, David DeAngelis, Hasrat Godil, Chris Jones, for giving me happy memories throughout the lab life. Also, there are the former labmates, Dung Lam, Tom Graser, Marcelo Vanzin, Ryan McKay, Bill McMillan. I also want to thank my committee members for all of their support and feedback on my research. I very much appreciate the time they take to evaluate my dissertation.

FROM PARTNER SELECTION TO COLLABORATION IN INFORMATION SHARING MULTI-AGENT SYSTEMS

Publication No._____________

Jisun Park, Ph. D

The University of Texas at Austin, 2006

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This research advances distributed information sharing by equipping nodes (e.g., software agents) in a distributed network with (1) partner selection algorithms in cooperative environments, and (2) strategies for providing and requesting information in competitive environments. In cooperative environments, information providers are willing to provide requested information, but information consumers must consider uncertainty in the quality of provided information when selecting appropriate information providers. In competitive environments, if a self-interested agent can be an information consumer and provider at the same time, agents need to determine the best ways to request and provide information so that the information acquisition utility can be maximized. This research defines a set of metrics for evaluating information acquisition utility, and presents a game-theoretic approach for determining the best information sharing strategies based on stochastic games. The results show how agents build collaborative relationships with appropriate agents and how the information acquisition utility is affected by those relationships.

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CHAPTER 1

INTRODUCTION

"Non-cooperation with evil is as much a duty as is cooperation with good."

- Mohandas Gandhi

1.1 MOTIVATION AND RESEARCH QUESTIONS

This research presents information sharing strategies among distributed software agents to maximize each agent's information acquisition utility. The information sharing strategies enable agents (1) to efficiently select appropriate information providers in cooperative environments in the presence of information quality uncertainty, and (2) to build collaborative relationships with appropriate agents by adjusting information request supply strategies in competitive environments.

In cooperative environments, agents share a common goal(s) and cooperate with each other to pursue the shared goal(s) [Lesser 1999]. Therefore, in cooperative information sharing networks, information provider agents are assumed to always provide requested information since the information requests are made toward goal achievement and information supply helps accomplish the goals. However, the provided information may contain uncertainty in its quality, which can cause the degradation of information acquisition utility. Therefore, information consumer agents may want to select the best information providers (called *partners* in this research) who can contribute the most to their information acquisition utility. On the other hand, in competitive environments, each agent has its own goal(s) [Leyton-Brown 2003]. Therefore, in competitive information sharing networks, information provider agents may not provide requested information. The supply of information can occur only when the information supply benefits information provider agents. The expected benefits for information provider agents may include immediate payoffs such as monetary compensation or reciprocal information supply in the future. If immediate payoff to information provider agents is not granted, the interaction between information consumers and providers needs to be repeated for information supply to happen. If the interaction is not repeated, no agent will provide information to others because there is no expected future benefit from providing information to others by wasting their resources. If interaction is repeated, each agent can provide requested information expecting reciprocal future benefit. Consequently, each agent needs to determine its strategies for requesting information and responding to other agents' requests in a way that each agent's information acquisition utility can be maximized through the repeated interactions.

In this research, the distributed entities referred to as "agents" may be human or software agents. Characteristics of software agents mimic human's .proactive pursuit of goals and therefore offer an ideal modeling paradigm for addressing the challenges in (1) selecting the appropriate information providers in cooperative environments, and (2) determining information request and supply strategies in competitive environments. An agent is an intelligent entity pursuing goals with a certain degree of autonomy in its environment. Although a universal agreement on the essential features of agents does not exist, the following properties are commonly accepted as key ingredients of agents [Jennings, Sycara et al. 1998].

- *Situated*: Agents are deployed in or surrounded by environments. Typical examples of environments can include the Internet for information agents, a soccer field for robot soccer, a battlefield for combat agents, an e-market for buying or selling agents. In addition to the surrounding world, environments also include other agents.

- *Reactive*: Agents take sensory inputs from environments and respond to fluctuation in environments.
- *Proactive*: Agents are goal-oriented or goal-driven, so the actions or decisions agents make are not merely responsive but rather they strive toward goal achievement.
- *Social*: Agents are able to communicate and interact with other agents (including humans) to achieve goals, especially when multiple agents populate the environments.

As proposed in Sensible Agent architecture [Barber, Goel et al. 1997; Barber, Mckay et al. 2001], the primary tasks for achieving goals can typically be composed of sensing the environments, building situational pictures, selecting actions, and taking actions to environments, in addition to more complicated tasks such as structuring an organization, negotiating with each other, etc. Situational pictures, often called beliefs of agents, are built based on the sensory inputs which can be obtained either by direct sensing activity of an agent or by communicated data (information) from other agents (information providers). Information elements required to build beliefs are referred to as *information requirements*. Decisions on which actions to take are made based on the situational pictures. Thus, the goal achievement is affected by how accurately and efficiently the situational pictures are built.

In open and distributed environments where agents can join or leave their environments at will and where no central control exists, agents have goals of their own which they may not share with other agents, and each agent pursues its own goals in their environments. Agents are attributed to be *self-interested* when they are interested in achieving their own goals. Self-interested agents are competitive with each other because they compete for the resources in their shared environments. Even with the existence of system-wide global goals shared by all agents in the system, agents can be self-interested if the global goals are divided into sub-goals and the sub-goals are allocated to the agents as individual agent's goals.

Since an agents' goal achievement is affected by the situational pictures they build based on their perception of their environments, enhancing the ability to sense environments or to communicate information can help agents pursue their goals. When an agent is endowed with a complete sensing ability so that an agent can monitor or perceive all environmental changes, communication of information may not be indispensable. On the other hand, when an agent is bounded-rational, meaning an agent has limited resources and capabilities [Simon 1955], communications with other agents are critical to an agent's goal achievement. The communication of information can be assumed to be bidirectional since an agent can either provide information or request information. *Information exchange* or *information sharing* represents the bidirectional flow of information.

This dissertation aims to provide strategies to agents for sharing information with other agents efficiently, so that agents can find the most appropriate information providers as well as control the amount of collaborative efforts with other information seekers. The information sharing strategies are defined along two dimensions. The first dimension of the information sharing strategies is the strategy for requesting necessary information in an information consumer role. The information request strategy decides from which information providers to request which information elements, both in cooperative environments and competitive environments. The other dimension of the information sharing strategies is the strategy for responding to other agents' requests from an information provider role. This strategy determines the *degree of collaboration* with other agents. An agent's degree of collaboration with other agents adapts to its environments based on the agent's observations about other agents' behavior.

The ultimate objective of equipping agents with information sharing strategies is to enable agents to efficiently satisfy information requirements so as to maximize their own goal achievement in a given situation. The information sharing strategies maximize the agent's goal achievement by both inducing the emergence of collaboration among reciprocally complementary agents and by enabling agents as information providers to avoid exploitation. Agents are reciprocally complementary if an agent needs a subset of available information elements from the other agent, and the other agent needs a subset of available information elements from the agent in turn. In other words, collaboration emerges when agents can achieve more by sharing information with other agents than by operating without any interaction or communication. If agents are designed to respond to all requests from others, they can be exploited by selfish agents who try to obtain what they need without contributing to other agents. The proposed information sharing strategies can prevent the exploitation of information providers from selfish agents or selfish consumers.

The hypothesis of this dissertation can be stated as follows.

The information sharing strategies enable agents to obtain required information of high quality by building collaborative relationships with complementary and trustworthy agents.

The research questions to validate the hypothesis and corresponding challenges for each research question are as follows.

Research Question 1 (RQ 1) Partner Selection

How do information consumer agents select the most appropriate information providers so that information acquisition utility can be maximized?

In cooperative environments, information providers try to respond to information consumer agents' requests. Even if the information delivery is guaranteed to information consumer agents, the information acquisition utility can vary depending on the selection of information providers in the presence of multiple information providers. The uncertainty regarding information acquisition utility can stem from the deficiency of the providers in sensing, communication, or computation. The uncertainty can also be caused by a provider's attitude or resources; how much effort providers make in providing the information. From an information consumer agent's perspective, overcoming the uncertainties associated with information contributes to the agent's goal achievement. Also, an information consumer agent's information requirements can change over time due to the agent's level of autonomy or the dynamics of environments. This change in information requirements significantly affects the way that information is requested from others. This research question addresses the problem of how to incorporate the factors influencing information quality and the dynamic change of information requirements into a representation of the information acquisition utility, and how to select the providers who can maximize the goal achievability by maximizing an agent's information acquisition utility. In order to answer this question, we decompose the problem into the following sub-questions.

Research Question 1.1 (RQ 1.1): *How can information acquisition utility be defined?*

This research question identifies the key factors which can affect the information acquisition utility of an agent and provide a formal representation of the factors. Then, the information acquisition utility function is defined by combining those factors.

Research Question 1.2 (RQ 1.2): *How can information consumer agents find the most appropriate partners to maximize the information acquisition utility?*

By considering tradeoffs between the factors of information acquisition utility, agents pursue the maximization of the utility function. This research question addresses how agents can efficiently select the best information providers and investigate the tradeoffs of various selection schemes.

Research Question 2 (RQ 2) – Collaboration among Agents

How should an agent interact with other agents for sharing information?

The second research question addresses the issues of information sharing in more dynamic situations. In contrast to Research Question 1, this research question assumes competitive environments. Self-interested agents in the system pursue the maximization of their own benefits. The roles each agent can play are also extended by allowing consumer and provider roles at the same time. In other words, agents in the system play the role of information consumer and information provider at the same time, and try to maximize their information acquisition utility by controlling their own information request strategy and information supply strategy. When interactions are repeated, agents may need to provide information to others if the cost for providing information to the requesters is smaller than expected rewards in the future. This research does not assume any synchrony in information requests and delivery. Information requests and information delivery are asynchronous, meaning that each agent does not need to make decisions regarding information requests and information supply simultaneously. In other words, information requests are made whenever an agent needs information elements and a decision on information supply is triggered by other agents' requests, which are also made at arbitrary times. The asynchrony enables any two agents (agent 1 and agent 2) to be placed in one of the following relationships at any given moment; consumer-provider (agent 1 requests, agent 2 responds), provider-consumer (agent 1 responds, agent 2 requests), consumer/provider-provider/consumer (agent 1 requests and responds, agent 2 responds and requests simultaneously), and the relationship changes over time dynamically.

In order to provide information strategies that can handle these dynamic situations, Research Question 2 is divided into the following sub-questions.

> ***RESEARCH QUESTION 2.1 (RQ 2.1):*** *How should agents request information as information consumers?*
>
> In competitive environments, the information providers may respond to other agents' information requests based on their local decision process, thus the information delivery may not be guaranteed to information consumer agents. Also, the current information requirements are typically dependent on the previous responses of the providers because the current information requirements are the remainders which were not satisfied in the previous round of interactions unless the goal itself has changed. Thus, the information requests have to be made

in such a way that maximizes the agent's expected rewards, accounting for the interaction history and future expectation.

***RESEARCH QUESTION* 2.2 (RQ 2.2):** *How should agents respond to other agents' requests of information as information providers?*

Even if an agent can provide certain information to requesting agents, the agent does not need to waste its resources by helping those agents unless the agent is altruistic. On the other hand, if providing information helps a provider's goal achievement, it is a rational behavior to provide requested information, assuming the provider is self-interested. Therefore, the dilemma an information provider confronts is that if an agent is willing to respond to any requests, the agent can be exploited and may end up achieving nothing while if an agent does not respond to any requests the agent may not procure necessary information elements from other self-interested agents. Therefore, agents need to adaptively control the way they respond to other agents' requests.

***RESEARCH QUESTION* 2.3 (RQ 2.3)**: *How can the strategies for information consumers and information providers be related?*

Since an agent is an information provider and consumer, the strategy as an information provider can affect the strategy as an information consumer and vice versa. As an example, an agent is likely to make requests to the agents which it thinks it has formed collaborative relations with, and the agent's degree of collaboration with those agents can give clues for the request decisions. Therefore, agents can benefit from properly coupling both dimensions of the information sharing strategies.

1.2 APPROACH OVERVIEW

This section presents the overview of approaches for each research question. More details about each approach are presented in Chapters 3 and 4.

1.2.1 Partner Selection

An information consumer agent has a set of goals and the goals impose a set of information elements required to achieve the goals. The information requirements (i.e. a set of information elements required by goals) need to be satisfied from other information provider agents. An information consumer agent evaluates the information providers and selects the information providers which can contribute to the consumer's rewards.

Rewards from information acquisition (i.e. information acquisition utility) are defined in terms of cost, coverage, and quality, which account for the computational burden of information exchange, the amount of information requirements satisfaction, and the error in the obtained information respectively. Information acquisition needs to be computationally inexpensive. The acquired information needs to contribute to the information requirements so that more requirements are satisfied by the acquired information. In addition, the information needs to be of high quality, meaning the information needs to be accurate and consistent.

The dilemma for an information consumer is that the highest quality information may require the most computational cost, or coverage can sometimes be maximized by low quality information. These tradeoffs are compromised by defining a combined measure of information acquisition utility. The information consumer agents aim to select the information providers who maximize the combined measure of information acquisition (i.e., the reward of information acquisition). The process of information acquisition from an information consumer agent's perspective is depicted in Figure 1.

The repeated interactions with providers enable agents to update the evaluation of information providers, and the selection can be refined over time. Also, the iterative refining of information providers can make information consumer agents accommodate system dynamics.

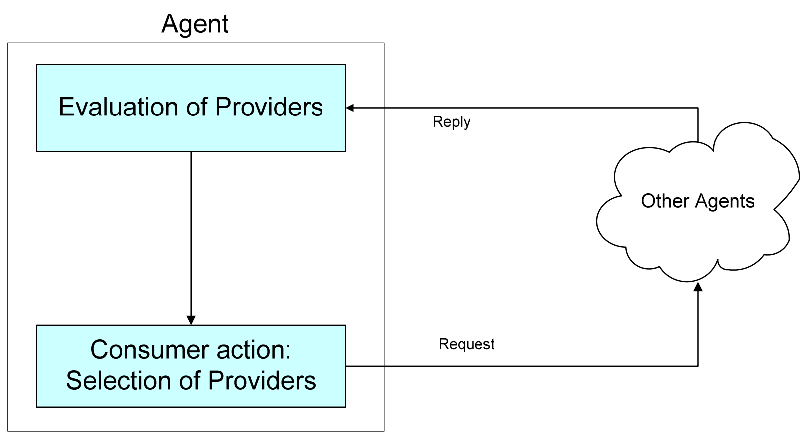

Figure 1 Partner Selection

1.2.2 Collaboration among Agents

In competitive environments, agents do not usually share their internal states or decision-making process with others. Therefore, agents need to model other agents' internal states or decision-making process by observation. This research provides a scheme to build the model of other agents' actions for information sharing, and use the model for the decision-making process. In this research, the decision to share information, called information sharing strategies, consists of two action sets. The first type of decision for information sharing determines from which information providers to request which information. Since information providers have choices as to whether to respond to the requests and information consumers do not know the providers' information sharing strategy, information consumer agents model the information providers' information sharing strategy by observing the responses of information providers. The second type of decision for information sharing determines the degree of collaboration. The degree of collaboration determines how agents respond to other agents' requests. Figure 2 depicts how an agent decides the information sharing strategies as a consumer and a provider by observing other agents.

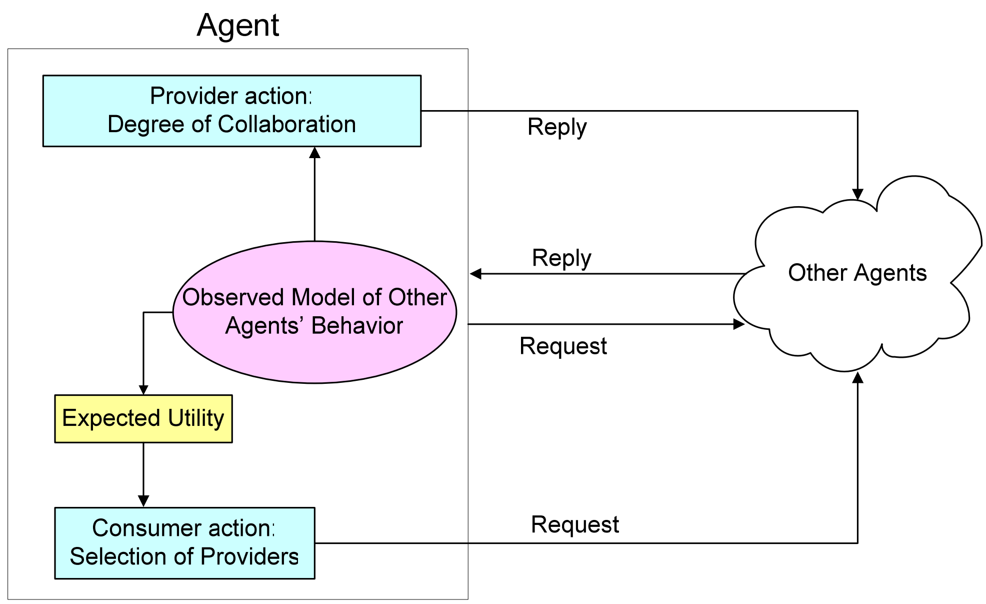

Figure 2 Collaboration among Agents

An agent's strategy as an information consumer is determined by modeling the interaction as a stochastic game. In the stochastic game, each state is modeled as a set of information requirements. The available actions as a consumer at a state and providers' corresponding actions decide the next state. For example, with a consumer agent's initial state comprised of information requirements A and B, if a consumer's action is to request information A and B from agent 1 and agent 2 respectively, the next state of the consumer agent with providers' action such that agent 1 responds and agent 2 does not respond is information requirement B. Thus, the consumer agent needs to decide from whom to request information B in the next step. A consumer agent calculates the sequence of actions such that all the information requirements are obtained, and selects the current request actions that maximize the expected rewards. When calculating the expected rewards, the probability of transition from one state to another state is dependent on the providers' actual actions, and the probability is modeled from the previous history. Also, the quality of the information as trustworthiness is reflected in expected rewards.

An agent's strategy as an information provider is to determine the degree of collaboration with the requesting agents. The degree of collaboration is the probability of responding to other agents' requests. When two agents are in the role of providers with each other (i.e., two agents request information from each other), the expected reward structure becomes similar to the Prisoner's Dilemma (PD) [Axlerod 1984], with a continuous action space for each agent. Since the interaction is assumed to be repeated, the problem is extended to the Iterated Prisoner's Dilemma (IPD) [Axlerod 1984]. Each agent has binary choices in IPD, and Tit-For-Tat (TFT) has been the most powerful strategy for accumulating the maximum rewards in IPD. TFT is to start with cooperation and do the same action with the opponent from the next interaction.

The adaptive degree of collaboration proposed in this research also takes a similar approach. A consumer agent starts from a high degree of collaboration. The degree of collaboration decreases if the interacting agent's degree of collaboration decreases, while the degree of collaboration increases if the interacting agent's degree of collaboration increases. Since the other agents' degree of collaboration is not known, each agent builds a model of the other agents' degree of collaboration based on history of interaction, and uses the model for inferring the other agents' degree of collaboration. An agent can also be in a provider's role when there is no bidirectional interaction. For example, when agent 1 does not request information from agent 2, agent 2 may request information from agent 1. In that case, they are not playing IPD, so continuous variation of TFT is not applicable. Thus, if agent 1 does not adjust its degree of collaboration with agent 2, agent 2 can exploit agent 1 by requesting information from agent 1, because agent 1 does not adjust (.i.e., decrease) the degree of collaboration with agent 2, which is not desirable to agent 1. This situation is addressed by introducing the decay of the degree of collaboration. An agent decays the degree of collaboration if it does not request information from particular information provider.

1.3 SUMMARY OF CONTRIBUTIONS

The contribution of this dissertation by answering the research questions and validating the hypothesis can be summarized as follows.

- *Defining the information acquisition utility based on goal achievement*: This research provides a model of the information acquisition utility based on each agent's goal achievement. Instead of deploying an incentive-based utility model (e.g., [Ioannidis, Ioannidis *et al.* 2002; Yu and Singh 2003b]), which usually involves a monetary transfer mechanism among agents or assumes the allocation of payoff from the system, the proposed information acquisition utility is determined according to each agent's needs and the delivery of information derived from each agent's goals. This information acquisition utility, defined from each agent's perspective, not only removes the need for a complicated incentive mechanism, but also allows the different implications of information exchange from agent to agent based on the agents' information requirements. Thus, this alternative approach provides a more fundamental element for representing goal achievability, especially in distributed multi-agent systems.

- *Providing partner selection schemes in cooperative information sharing networks:* The proposed partner selection schemes use the proposed information acquisition utility as the selection criteria for information providers in cooperative environments. In a single provider selection problem, a consumer agent may not suffer from the search space explosion and can pursue the selection of the optimal combination of information providers. Heuristic search techniques are proposed to allow the agents to find the good-enough solutions for the cases that can cause search space explosion, such as the multiple provider selection problems. The heuristic search techniques speed up the search by escaping the local optima or plateau quickly and lead a consumer agent to "good-enough" partner selection swiftly with a limited amount of resources. The fast convergence to the "good-enough" partners also improves information acquisition utility in dynamic environments.

- *Providing the information sharing strategies for dynamic and asynchronous information exchanges*: Information exchange is not a synchronous one-shot event, but more likely to be asynchronous and continually active. In other words, agents request required information if necessary and respond to other agents' requests when other agents actually request information. Also, the information requirements can change due to goal change or other dynamics of environments. These complexities are dealt with to provide agents with information sharing strategies that can maximize agents' information acquisition utility. As opposed to other research results which mostly focus on either the information consumer's perspective or the information provider's perspective (e.g., [Saha, Sen et al. 2003; Sen, Dutta et al. 2003]), the proposed information sharing strategies contemplate both consumer and provider roles at the same time.

- *Showing the emergence of collaboration among agents and exploitation avoidance*: As an essential feature of information sharing strategies, this dissertation shows how collaborative relations among competitive agents can emerge. In addition to complementary relations between agents, this research incorporates the trustworthiness of information providers as another factor that affects the construction of the relationships. It is also shown how collaborative relations can help avoid the exploitation of information providers by selfish agents. Finally, as opposed to the explicit agreement-based collaboration schemes, the emergent nature of the collaborative relationships allows the flexibility of constructing new relationships easily in the presence of any environmental dynamics.

The remainder of this dissertation is organized as follows. In Chapter 2, related work is presented. Chapter 3 provides the approach for the partner selection problem, followed by strategies for collaboration among agents in Chapter 4. Chapter 5 presents experimental results for each research question. Chapter 6 summarizes and concludes the dissertation.

CHAPTER 2

RELATED WORK

This chapter presents previous work related to the research questions: (1) partner selection and (2) collaboration among self-interested agents.

Research on partner selection (often called the connection problem [Davis and Smith 1983]) can be further categorized from different perspectives depending on the techniques for modeling other agents and interaction styles. The ways agents model other agents give criteria for evaluating appropriateness. Once the evaluation metrics for partner selection are decided, how the evaluations are used to select appropriate partners needs to be decided.

Research on collaboration among agents is a natural extension of partner selection. While the partner selection problem generally assumes unidirectional provider-consumer relationships and aims to equip information consumers with partner selection strategies, collaboration is generally a bidirectional relationship. In cooperative environments with globally shared goals, collaboration among agents may imply a team formation. On the other hand, in competitive environments with local goals for each agent, the collaboration may emerge as a result of agents' efforts to maximize individual payoffs. In other words, agents' collaboration can emerge if collaborative interactions are chosen for higher expected payoffs as a result of the decision-making process.

In the following sections, previous work in each research question and related research are presented and compared to the research presented in this dissertation.

2.1 PARTNER SELECTION

Partner selection is a core capability for agents in distributed networks where agents cannot achieve their goals by themselves or where they can do better jobs when they can get help from other agents. In other words, partner selection plays an important role in filling the deficit of distributed agents. Research on partner selection generally proposes various types of evaluation metrics for selecting appropriate partners. The evaluation metrics are called trustworthiness, quality of service, etc. Partner selection mechanisms can in general be divided into three categories based on the interaction styles (note that these three categories are not strictly divided): local decision with local modeling, negotiation-based approach (i.e., coalition formation), and middle agents.

Local decision with local modeling [Nebel 1998; Barber and Park 2004b; Park and Barber 2004; Maximilien and Singh 2005; Park and Barber 2005b] takes into account the local model about potential partners (i.e., trustworthiness, reputation, quality of provided services) and finds the most appropriate partners based on the local model. This approach involves the evaluation of service or service providers, and the evaluation is in general not a global knowledge. The negotiation-based approach involves explicit peer-to-peer communication for negotiation. The Contract Net Protocol [Smith 1980; Smith and Davis 1981] provides a simple and efficient negotiation mechanism for finding the best partners who provide necessary services at the least cost. Research on coalition formation among self-interested agents often adopts the negotiation mechanism so that agents can figure out who the best candidates are for forming a coalition. Negotiation is useful especially when there are no arbiters. Using middle agents [Decker, Sycara et al. 1997] can also be listed as another type of partner selection mechanism. Brokers or matchmakers are often deployed to facilitate the process of connecting service providers and service consumers.

The selection method in this dissertation can be categorized as local decision by modeling agents. However, this method is different from other local decision approaches in the way that the quality of service is evaluated based on the contribution to an agent's goal achievement in a dynamic environment. In the following subsections, more details about each category of partner selection mechanisms are provided.

2.1.1 Local Decision by Modeling Agents

In order to select appropriate partners, agents need to know about other agents' degree of appropriateness. Because of the lack of global knowledge about entire systems, self-interested agents need to build their own models about other agents and the world. These models are constructed either by direct observation or communication with other agents. The models for gauging the appropriateness of other agents as partners are usually based on the evaluation of information providers in terms of predefined appropriateness.

Research on the evaluation of information providers has been conducted in the context of social control. In social control research, agents need to evaluate other agents or the services provided by other agents in order to realize a distributed but secure control over the interactions among agents [Rasmusson and Jansson 1996]. Rasmusson and Jansson suggest the use of *social control* as a way to create secure open systems. The idea is to let the agents in the system be responsible for the security of the system without having a global authority. There has been a significant amount of literature related to social control, with trustworthiness research [Alchourron, Gardenfors et al. 1985; Barber and Kim 2001; Hyunh 2006] representing the most relevant area for social control.

Research addressing trust in an agent society provides various perspectives for evaluating other agents as well as the methods for identifying the most potentially trustworthy partners. However, since the trust research mostly focuses on modeling and evaluating the trustworthiness of the agents, research about how the trust models can affect goal achievement in a dynamic environment has not been fully explored. This dissertation demonstrates how agents can proactively pursue their goals using an estimated model of other agents in a dynamic environment, as well as how agents can establish collaborative relationships.

In the information exchange domain, research on belief revision also involves how to select appropriate information providers. Belief is in general a situational awareness, and research investigating belief revision in multi-agent systems [Alchourron, Gardenfors et al. 1985; Shafer and Shenoy 1990; Barber and Kim 2003; Fullam and Barber 2004] pursues a similar objective: build the agents' beliefs accurately and efficiently by using all the information provided. In these approaches, the beliefs are assigned preferences by epistemic relevance in a symbolic logic [Alchourron, Gardenfors et al. 1985], or ordered by credibility in [Shafer and Shenoy 1990] using belief function. Also, preferences can be determined by evaluating the information source trustworthiness using Bayesian networks [Barber and Kim 2003] or a statistical approach [Fullam and Barber 2004]. Exact inference using these approaches is computationally expensive [Liberatore 1997; Nebel 1998; Lerner, Segal et al. 2001], so there have been approximate inference approaches which reduce the complexity of computation [Cadoli and Schaerf 1995; Koller, Lerner et al. 1999; Murphy 1999; Chopra, Parikh et al. 2000]. However, those approximate inferences are applicable to the specific belief revision algorithm targeted by the respective scheme.

The partner selection scheme proposed in this research does not consider how the belief should be formed, but it can be used before the belief revision process to vet information and sources on which the belief revision process relies. Therefore, the proposed scheme in this research is independent of the belief revision schemes, while we hypothesize that the research will enhance the efficiency and accuracy of the belief revision process by reducing the amount of information as well as increasing the quality of information the belief revision process handles, which results in the increase of goal achievability.

Maximilien and Singh [2005] proposed a method for selecting appropriate service providers based on quality of service (QoS) among Web services. They distinguish interactions of service providers and consumers into three phases: discovery, selection, and binding. For the selection phase, they associate nonfunctional attributes such as capacity of a service, and response time to represent the quality of services. The quality of services can be provided as a reputation and is shared by all agents. With this evaluation of service quality, the selection problem can be simplified to picking up the most trustworthy services. While this approach provides a practical solution to selecting the most trustworthy partners based on the quality of Web services, it lacks the ability of handling dynamic changes in service consumers' requirements. In other words, Maximilien and Sigh's approach can work well for a one-shot interaction or iterated interactions for a single service, but it does not consider the case where the current or future service requirements are dependent on the previous interactions. In order to overcome this limitation, the proposed approach in this dissertation uses expected utility, which is based on the behavioral model of service-providing agents as well as the quality of services.

Generally, modeling other agents by observation and making local decision about who to work with do not involve a negotiation process that requires an agreement among the participating agents. Therefore, local decision by local modeling is adaptive to any dynamics in the system. Also, since the decision is made locally, it is relatively simple to construct an overlapping relationship. However, because of intrinsic uncertainty from the local model, the accuracy of the local model significantly affects the resulting selection of partners. In addition, agents need iterative interactions to gather evidence or to build a knowledge base for modeling or evaluating other agents.

2.1.2 Negotiation-based Partner Selection

Making agreement in agent partnerships with other agents can be accomplished through a negotiation process. Because of the clear memberships in collaboration, negotiation among agents can give a stable and stationary relationship especially for long-term interactions.

Contract Net Protocol (CNP) [Smith 1980; Smith and Davis 1981; Davis and Smith 1983] provides a simple and efficient negotiation mechanism for finding the best partners who provide necessary services at the least cost. CNP is a fully automated negotiation protocol where each agent can be an initiator or a participant. After an initiator sends out a call for proposals, participants bid on that call and the initiator selects the best bids while rejecting other bids. This protocol has been adopted in TRACONET (Transportation Cooperation Net) [Sandholm and Lesser 1997] for a vehicle routing application, and has also been standardized in FIPA (Foundation for Intelligent Physical Agents) as an interaction protocol among agents. Although CNP provides a relatively simple mechanism for partner selection, it can still be computationally expensive in large-scale systems because of the message complexity. Also, CNP may be vulnerable to the situation where commitment to the contract is not guaranteed. In other words, agents need to be cooperative for CNP to work.

The Adaptive Decision Making Framework (ADMF) [Barber and Martin 2001] also deploys a negotiation-based partner selection scheme. Agents implementing ADMF are able to dynamically reorganize the structure of a group of agents to meet the needs of their current situation. ADMF provides a spectrum of power relations between agents, from locally autonomous to master-slave. By dynamically changing the decision-making framework through negotiation, agents can find whom to work with and how to work with them. ADMF allows a dynamic adjustment of agents' relationships but because of the complexity of the negotiation process ADMF can suffer a scalability problem in a large-scale system. Also, due to the assumption about commitment to the agreement, the agents are assumed to be cooperative. Especially, ADMF is designed for a system where agents have shared global goals and the structures among agents are targeted to maximize these global goals.

Coalition formation seeks to partition the agents in a system into groups which maximize the utility of the group or the individual agent. The partitioning of the agents is usually modeled as a characteristic function game and involves three activities [Sandholm and Lesser 1997]: coalition structure generation, solving the optimization problem of each coalition, and pay-off division. Among these three activities, coalition structure generation and optimization are closely related to finding appropriate partnerships from a set of potential groupings. Pay-off division is to decide how the utility gained by forming a coalition should be distributed among the agents to keep the coalition stable. While pay-off division has been a major issue in the coalition formation research and is useful for maintaining or encouraging agents' collaboration, recent focus has been on coalition structure generation [Banerjee and Sen 2002; Klusch and Gerber 2002; Dutta and Sen 2003; Dang and Jennings 2004] in addition to the earlier research [Ketchpel 1993; Shehory and Kraus 1995; Shehory and Kraus 1996; Sandholm, Larson et al. 1998].

Generally, the formation of a coalition involves the negotiation process [Ketchpel 1993]. Ketchpel identified four phases of coalition formation which are the communication phase, calculation phase, offers phase, and unification phase. The communication phase locates other agents that may have compatible or overlapping goals, or agents that may have complementary skills. When an agent communicates with potential partners, the information which is necessary to calculate the Shapley value [Shapley 1953b] is delivered to the potential partners. The Shapley value represents each agent's aggregated contribution to the coalition, and the value is dependent on the order of agents joining the coalition. In the calculation phase, the Shapley values for each permutation of the coalition structures are calculated. Calculation of the Shapley values for all the permutations is an exponential operation, so the calculation is limited to pairs of agents only. Each agent creates a preference ordering of the partners based on the calculated Shapley value. In the offers phase, the matching is decided using a modified stable marriage algorithm [Shapley 1953b]. When a pair of agents forms a stable matching, they form a coalition in the unification phase, and in the next round of communication, the coalition acts as a single agent. This process of interaction and negotiation to form a coalition makes the membership global to the agents, meaning the agents, at least in the same coalition group, know who is in the group.

On the other hand, partner selection in this research gives a local perspective of partnerships, meaning that only the information consumers know who is partnering with them. In addition, instead of having an explicit negotiation process – including the Ketchpel's communication, calculation, offers, and unification phases to obtain cooperation agreements – this work takes a different approach when attempting to motivate cooperation so that partners are ready to affirmatively reply to requests and enter into partnerships.

Most of the coalitions are disjoint [Ketchpel 1993; Shehory and Klaus 1995; Sandholm, Larson et al. 1998; Banerjee and Sen 2002] except Shehory and Kraus

[1996]. Shehory and Kraus provide an approach to allow overlapping coalitions, meaning an agent can be a member of more than one coalition. The overlapping membership is possible via the precedence ordering of goals, and it reduces the waste of resources and capabilities.

Because of its local perspective, the partner selection scheme in this research always allows overlapping partnerships. Overlapping partnerships are useful in the information domain because the information is duplicable. Agents can provide the same information to multiple consumers, and can also handle multiple instances of information.

Although Klusch and Gerber [2002] investigate the coalition formation in an open and dynamic environment, the resulting coalition is stationary. The stationary coalition does not reflect the fluctuation of the environment. Barnerjee and Sen [2002] also proposed a stationary coalition formation based on pay-off structure and probability of the pay-off. Barnerjee and Sen [2002] assume that there are a finite number of interactions, and find the static partnership during the given number of interactions. These stationary coalition structures do not work in an open environment. The "best" coalition structure at one point in time may no longer be the best one in the near future. Therefore, dynamic coalition structure or partnerships are necessary to adapt to the environment, and are investigated in this work.

The coalition formation process is also computationally expensive. For example, the stable marriage algorithm [Ketchpel 1993] or set covering algorithm [Shehory and Klaus 1995] used to find the best coalition structure requires a significant amount of computation. Some research focuses on the efficiency of the coalition structure generation [Sandholm, Larson et al. 1998; Dang and Jennings 2004]. Sandholm et al. [1998] focused on the resource-bounded agents and proposed an anytime algorithm, which has the worst case bound. Dang and Jennings [2004] improve the efficiency of Sandholm's algorithm while keeping the worst case bound guarantee.

Some of the approaches assume super-additivity [Ketchpel 1993; Shehory and Klaus 1995], which may not hold in the real-world problem. There are costs for forming a coalition, and this cost should be taken care of. The proposed approach in this research takes care of the cost incurred by interacting with information sources by considering the tradeoffs between the benefits gained by the partnership and the costs of interaction.

In summary, negotiation-based partner selection is generally computationally expensive, and requires a clear agreement about the relationships. Also, because of the computational burden and the requirement of agreement, agents may not be able to dynamically change partners. In addition, agents in a system need to share a common protocol or language. However, clear memberships help reduce uncertainty about partner selection, and can also provide stable and stationary relationships for long-term interactions.

2.1.3 Middle Agents

Middle agents [Decker, Sycara et al. 1997] provide a way of finding appropriate partners. A middle agent is an arbiter who actually helps agents find partners based on preferences or capabilities. Based on the explicit privacy concerns, middle agents can be categorized into anonymizer, matchmaker, recommender, arbitrator, broker, blackboard, introducer, etc. In other words, according to the degree of sharing of the information about preferences of requesters and the capabilities of providers, the role of middle agents can be different. However, the basic idea behind the middle agent is to deploy designated help provider in finding appropriate partners. Middle agents have been used in various application areas such as service discovery, lookup solutions for peer-to-peer networks, information retrieval, referral network, and Web-services (e.g.,[Ratnasamy, Francis et al. 2001] [Garofalakis, Panagis et al. 2004] [Yu and Singh 2003a] [Ludwig and Santen 2002] [Trastour, Bartolini et al. 2001]). While middle agents provide a practical solution for partner selection, the agents who want to contact the middle agents need to follow the communication protocol, which may not be always available for every agent. Also, a single point of failure from a single middle agent can cause a problem although it is possible to use various fault-tolerant schemes. Scalability is another issue, but hierarchical middle agents can improve the scalability to some degree.

In the following sections, related work to the collaborations among self-interested agents is presented. A game-theoretic approach for promoting collaboration as well as payoff division in coalition formation has been investigated in the literatures. A reciprocity-based approach and free-rider avoidance in peer-to-peer networks are also presented.

2.2 COLLABORATION AMONG SELF-INTERESTED AGENTS

Research on collaboration and cooperation among self-interested agents focuses on (1) how self-interested agents can be encouraged to collaborate and (2) how each agent can decide on the strategy for collaboration.

In seminal work by Axelrod [Axlerod 1984], it is shown that cooperation can emerge in a world of self-interested entities based on reciprocity and that the emerging cooperation is stable if the interaction is for long enough. The problem of encouraging agents to collaborate is also addressed in coalition formation (team formation) and incentive/penalty mechanisms in peer-to-peer systems. In coalition formation, in addition to determining memberships of agents, fair distribution of profits (i.e., payoff division) for stable coalition has been addressed in a number of studies. Incentive/penalty mechanisms in peer-to-peer systems induce self-interested rational agents to contribute to the system. By granting incentives to more collaborative agents and penalizing selfish agents, free-riders or whitewashers can be avoided.

In addition to promoting collaboration, the problem of selecting the best strategies for collaboration has been addressed from different perspectives. The challenge for best strategy selection comes from local situational awareness. Because of the limit on perceiving other agents' strategies in competitive environments, the strategy of collaboration affects the performance of individual self-interested agents.

In the following sections, previous work on collaboration among self-interested agents is provided, and discussion about the relationship with this research is presented.

2.2.1 Game-theoretic Approach for Collaboration

Motivating collaboration is meaningful to self-interested agents only if interactions are repeated. In repeated interactions, self-interested agents can expect future benefits of collaborating with others. As a framework for modeling interactions among agents and to develop a mechanism to promote collaboration, game theory has been widely deployed.

Axelrod [1984] investigated a model of cooperation based on the Iterative Prisoner's Dilemma (IPD). The Prisoner's Dilemma (PD) is a type of general-sum game where two players can have the choice to either cooperate or defect. Each player in a PD game is interested in maximizing its own rewards. The reward structure in generalized form is shown in Table 1, where the left element in each cell is a reward for player 1 and the right element is a reward for player 2, with the relationship among rewards satisfying the inequalities T > R > P > S.

In a one-shot PD game, defecting gives a higher payoff no matter what the other agent’s action is. Therefore, if all players are rational, they will select defect. However, in repeated interactions, a Tit-For-Tat strategy by Anatol Rapport, which starts from cooperation on the first move and do the same as the other player’s action from the next move, has been shown to be the most powerful [Axlerod 1984]. Tit-For-Tat gives a chance to punish a non-cooperative player in the following move, and the optimal choice can move to cooperating. The research in this dissertation adopts a variation of Tit-For-Tat for continuous action space as a strategy for information providers, because the action space for agents from a provider’s perspective is defined as continuous.

Table 1 Reward Structure for Prisoner's Dilemma

	Player2		
Player1		Cooperate	Defect
	Cooperate	R, R	S, T
	Defect	T, S	P, P

Azoulay-Schwartz and Kraus [Azoulay-Schwartz and Kraus 2001, 2004] suggest a stable strategy for information exchanging agents from a provider’s perspective. They modeled information exchange as a stage game so that a consumer and a provider take turns. A variation of Tit-For-Tat was proposed as a strategy profile by taking into account the previous action history. Modeling information exchange as a stage game can be reasonable in a synchronized message passing system. However, in general, message passing among agents may not be assumed to be always synchronized. Agents can request information any time they need, and the requests can also be made asynchronously. Also, Azoulay-Schwartz and Kraus assume a single information element and two players, meaning their modeling and analysis assume a single type of information between two agents, while different types of information requests from multiple agents can occur in multi-agent systems. In addition, the assumption that interactions with multiple agents can be explained by applying the two-player game multiple times may not work in more complex situations because of the dependence of information and different reward structure for different situations.

The research in this dissertation adopts a stochastic game theory so that providers' actions and consumers' actions can be considered together while accommodating the changes of the information requirements. Also, by deploying the stochastic games, interactions for multiple information elements with multiple agents can also be taken care of. In addition, this research does not assume that the information from information providers is always true. Regardless of the intention of information providers, the provided information can be faulty and can contain errors. The errors can be either from information providers' incapability, or generated intentionally by the providers. In order to take care of the accuracy and consistency of the provided information, this research introduces a trustworthiness measure into the reward function.

2.2.2 Coalition Formation – Payoff Division

Coalition formation has been an important issue both in cooperative and competitive agent systems [Kahan and Rapoport 1984]. In a cooperative environment, agents in a coalition pursue the maximization of social or global utility, and the agents stay in the coalition as long as global utility can benefit from the coalition. In competitive environments, the stability of coalition is affected by a payoff division scheme since each agent is self-interested and tries to maximize its own utility. The question of how social goods (i.e., payoff) from forming a coalition can be divided or distributed among participating agents so that agents are motivated to stay in a coalition has been investigated in a number of studies.

In the early literature by Kahan and Rapoport [1984], the payoff to a coalition is distributed to each agent, with the expected payoff for each agent equal to the Shapley value. Calculating the Shapley value is computationally expensive and it is difficult to find the optimal distribution in large-scale systems. Also, in order to use the Shapley value, it is assumed that agents have the common knowledge on the value of coalition. In more realistic situations, the expected payoff of each coalition structure, thus the expected payoff to each agent, can differ for different agents. Ketchpel [1994] addressed this problem with the *Two Agent Auction* mechanism. The purpose of the *Two Agent Auction* is to solve the division of utility or payoff in the presence of uncertainty. When two agents form a coalition of size 2, they play the role of one agent, and the auction repeats until the optimal coalition is established.

Sandholm and Lesser [1995] address the issues of coalition formation in terms of optimality and stability. While the optimality of a coalition looks at the structure of coalition in super-additive environments, the stability of a coalition is investigated as a payoff distribution problem using the solution concept of the *core*. The *core* is a set of vectors, where each vector in the *core* represents payoff to the agents such that agents are not able to be better off by leaving the coalition structure. Building a coalition under the solution concept of the *core* enables agents to be motivated to construct a stable coalition, but this requires a significant computation and common knowledge about the solution concept.

Shehory and Kraus [1999] deploy the solution concept of the *kernel* for stable payoff division. The *kernel* is a set of configurations where all coalitions in the configurations are in equilibrium. The equilibrium of a coalition is achieved when each pair of agents in the coalition is in equilibrium, meaning each agent cannot outweigh one another in the coalition. A coalition is kernel-stable (K-stable) if all the pairs of agents in a coalition are in equilibrium.

The computational burden of constructing a coalition can reduce the flexibility of building a new coalition in dynamic environments. Klusch and Gerber [2002] have developed a dynamic coalition formation scheme (DCF-S). In a DCF-S, each agent takes steps of preparation, simulation, negotiation, and evaluation, and agents form a potentially overlapping coalition in order to solve a set of cooperative games with stable payoff distribution.

In summary, cooperation can be induced by payoff division. If the payoff division scheme satisfies the agents, then the coalition is stable and the agents in the coalition can be motivated to cooperate with others to get their portions of the payoff. The basic idea for motivating the agents to cooperate is to give them a set of benefits. However, in an open environment, it is hard to know how beneficial the cooperation is to an agent. An agent's benefit or utility is dependent on the other agents' degree of cooperation as well as the agent's own degree of cooperation.

In information sharing networks, when the information sources (agents) are completely cooperative so they are willing to provide information whenever the information is requested, an agent gains the maximum benefit if the agent is completely selfish and requests all the required information from those information sources assuming no cost. On the other hand, if the requesting agent is completely cooperative and the information sources are also cooperative, so the agent does not request any information, the agent gains nothing from those sources and may not be able to achieve its goals. In addition, considering the information supply (the exchange of information between information suppliers and receivers) as a form of cooperation in the information domain, there is uncertainty in many aspects such as the information quality, cost of information delivery, etc. in an open environment, and an agent's benefit is affected also by those factors – quality and cost. Previous approaches do not take into account the quality of shared information although the utility is actually dependent not only on the amount of the information shared by others, but also on the quality of the information shared by others. The proposed work in this research takes into account the quality of the information shared by information providers for modeling the utility function for cooperation.

In addition to these payoff division schemes in coalition formation for encouraging collaboration, reciprocity-based approaches also aim to build collaborative relationships between self-interested mutually beneficial agents using bidirectional dependence.

2.2.3 Reciprocity-based Collaboration

Sichman et al. [1994] proposed a social reasoning mechanism using dependence networks. Dependence networks are used for defining the taxonomy of dependence situations and can be used for making up the capabilities of agents. A data structure called *external description*, which is composed of goals, actions, resources, and plans, is used to store the information about others, and the *external description* is used to build the dependence networks of each agent. While this approach provides a useful and descriptive mechanism for building collaborative relationships with others, the adaptation to dynamics of goal achievement (e.g. goal change, partial achievement) is not explicitly taken care of.

Saha ［2004］ and Sen et al. ［Saha, Sen et al. 2003; Sen, Dutta et al. 2003］ propose a decision mechanism for constructing collaborative relationships among self-interested agents based on expertise reciprocity. The decision mechanism aids in agents' decisions about whether to accept other agents' help requests for tasks or not. The decision is based on the cost metric from past interaction and expected future savings by reciprocal collaborative relationships. This work differs from the research in this dissertation in that this work assumes system-wide goals and focus on giving information providers' collaboration strategies, while the research in this dissertation provides strategies for both providers and requesters. Also, this paper uses a goal-oriented metric for designing the reward structure, while they consider the reduction of cost.

Peer-to-peer networks (P2P networks) do not have central authority to control each node in the network. This distributed nature of the environment and the openness that any agents can join the system make free-rider avoidance a significant problem in P2P networks. In the following section, the work addressing free-rider avoidance by providing incentives to collaborative agents is provided.

2.2.4 Free-rider Avoidance in Peer-to-peer Systems

Free riders are those who get the incentive without contributing to others. An example of a free rider might be one who does not share files with others but downloads what others provide in a peer-to-peer file sharing system. Free riding happens because sharing the files results in the allocation of the resources for others, and that can reduce the resources which could be dedicated to downloading other contributors' files. Most approaches to the free-rider problem are to give incentive to those who contribute, and this concept of incentive is modeled in a game-theoretic framework [Golle, Leyton-Brown *et al.* 2001; Lui, Lang *et al.* 2002; Burahgohain, Agrawal *et al.* 2003; Yu and

Singh 2003b]. In Golle, Leyton-Brown et al. [2001], an agent's utility is dependent on a variety of different factors including the size of the download, network variety, disk space used, bandwidth used, altruism, and the financial transfer. A micro-payment mechanism is deployed to realize the financial transfer and to encourage each node to balance what they take from the system with what they contribute to the system. In contrast to Golle, Leyton-Brown et al. [2001], the utility model in Burahgohain, Agrawal et al. [2003] adopted a probabilistic service differentiation using a benefit matrix. An agent's utility is determined by the amount of information shared by an agent's peer and the probability that the peer would accept the request from the agent. The costs for sharing are also considered and reflected in the utility model.

CHAPTER 3

PARTNER SELECTION

3.1 Overview

Agents can derive benefits by receiving help from other agents when the agents are not self-sufficient in satisfying their own requirements for goal achievement. When agents need a set of information elements but are not self-sufficient in information acquisition, information elements from other agents can increase the satisfaction of the information acquisition, thus the goal achievement.

In a system where agents are assumed to be cooperative, information providers are willing to provide requested information if available. Information requesting agents (i.e., consumer agents) need to select an appropriate set of information providers so that they can procure all the necessary information of high quality at the least cost.

This chapter provides an approach for enabling consumer agents with a set of information requirements to select the most appropriate information providers by defining a set of evaluation metrics for providers (Section 3.3.1) and by proposing search methods for finding the solution (Section 3.3.2).

3.2 Problem Statement

An agent's information requirements (RQ) are a set of required information elements for goal achievement. The agent with information requirements is a consumer agent. Provider agents have a set of available information elements (PR) which they can provide when requested. There can be multiple provider agents that can provide the same information elements. Figure 3 shows a typical example of the problem. In the figure, agent 0 requires 4 information elements (RQ(a_0)={B, R, G, O}) and provider agents (agents 1, 2, 3) have information available, respectively PR(a_1)={B, G, O}, PR(a_2)={R, G, O}, PR(a_3)={B, R, G}. Although provider agents are willing to provide requested information, the quality of the provided information can be different. Also, the cost for obtaining the same information elements may vary depending on information providers. Therefore, the consumer agent (agent 0) needs to select the best set of information providers for each information requirement so that it can maximize its goal achievability.

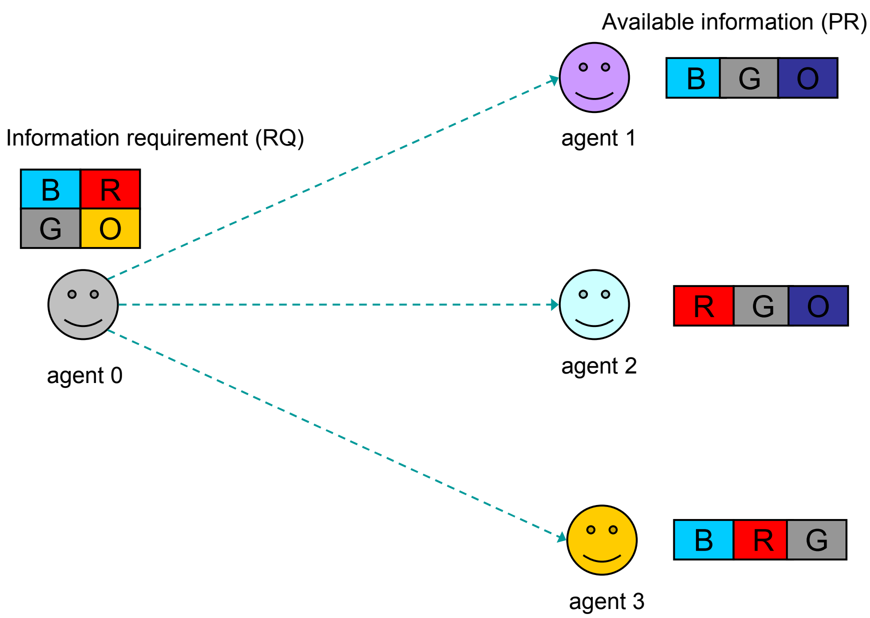

Figure 3 Example of the Partner Selection Problem

In general, a consumer agent's decision-making process can be represented by a finite state machine (Figure 4). A consumer agent has a single state of information requirements. Transitions are circular to the initial state since the interaction is repeated and the providers always provide requested information. The transition is triggered by the actions of the consumer agent (information requests) and replies from providers. In the repeated interactions, a consumer agent's objective is to acquire the most trustworthy information elements in terms of quality while maximizing the coverage of information requirements at the least cost (in other words, to request information from the providers such that $\underset{providers}{arg}(\max(Quality, Coverage) \wedge \min(Cost))$. The challenge for achieving this objective is that the quality of the provided information from each provider agent may not be known to the agent requesting the information. This challenge can be overcome by equipping consumer agents with the capability of modeling other agents. In other words, consumer agents can perform trustworthiness evaluation of provider agents.

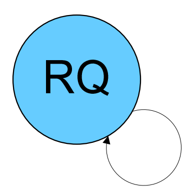

Figure 4 Finite State Machine for Consumer Agent's Decision Process

In the following sections, the details of provider modeling and evaluation metrics containing goal coverage, cost, and trustworthiness are provided, followed by the search methods for efficiently selecting the best set of providers.

3.3 APPROACH

This section provides an approach for enabling consumer agents with a set of information requirements to select the most appropriate information providers by defining a set of evaluation metrics for providers (Section 3.3.1) and by proposing search methods for finding the solution (Section 3.3.2)

3.3.1 Provider Evaluation

Provider evaluation metrics for partner selection – coverage, cost, trustworthiness – are provided in detail in the following sub-sections.

3.3.1.1 Coverage

Coverage represents the relevance of the information, and the relevance of a set of information from a set of information sources is decided by the degree to which the agent's information requirements are met [Barber and Park 2004a]. The following notation and assumptions are introduced in order to define the coverage metri:

- A consumer agent can have multiple goals ($G(a_i)=\{g_n\}$).
- Each goal g_n is assigned a weight $w(g_n)$.
- Each goal of an agent has a set of information requirements $R_{g_n} = \{r_k\}$.
- Information requirements from all goals constitute an agent's information requirements $RQ(a_i) = \bigcup_{g_n \in G(a_i)} R_{g_n}$.

The priority of an information requirement is introduced to describe the importance of each requirement or the relevance of requirements to goals. The priority of each information requirement is represented by $PRIO(a_i, r_k)$, and the assignment of priority value is decided by the consumer agent with the assumption that the information requirements are mutually exclusive. Higher priority is assigned to the information requirements which contribute to more goals. In that case, the priority of an information requirement is defined as follows:

$$PRIO(a_i, r_k) = \sum_{all\ n} \frac{w(g_n)}{|R_{g_n}|}, \quad r_k \in R_{g_n}$$

Given the priority of each information requirement, goal coverage by selecting a set of provider agents (*S*) as information providers is the portion of the priority sum covered by *S*. The coverage of selecting *S* is the average goal coverage for all goals. The following equations define the goal coverage and coverage:

$$GoalCoverage(a_i, S, g_n) = \frac{\sum_{all\ r_i} PRIO(a, r_i)}{\sum_{all\ r_j} PRIO(a, r_j)}$$

, where $r_j \in R_g$ and $r_i \in R_g \cap r_i$ is provided by S

$$Coverage(a_i, S) = \frac{\sum_{all\ g_n \in G} GoalCoverage(a_i, S, g_n)}{|G(a_i)|}$$

As an example of measuring coverage for selected provider agents, assume there are 4 agents as in Figure 5.

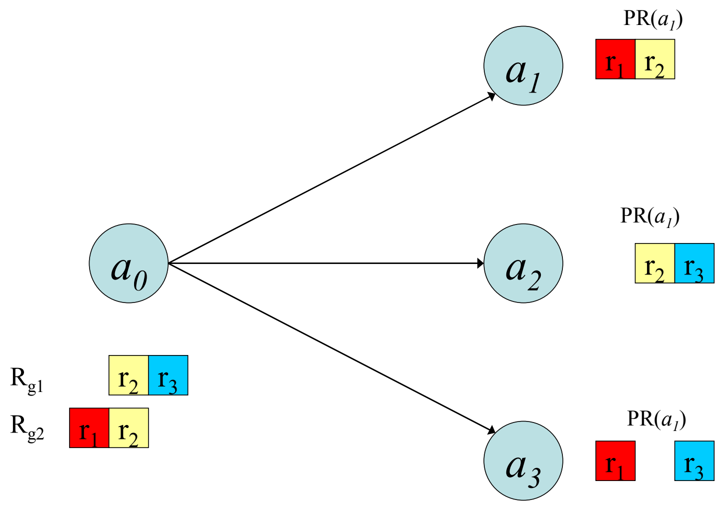

Figure 5 Coverage Example

In Figure 5, agent 0 is a consumer agent and has two goals (g_1, g_2) with information requirements of each goal, $R_{g_1} = \{r_2, r_3\}$, $R_{g_2} = \{r_1, r_2\}$ constituting agent 0's information requirement RQ(a_0)={r_1, r_2, r_3}. Provider agents (agent 1, 2, 3) have available information elements such that PR(a_1)={r_1, r_2}, PR(a_2)={r_2, r_3}, and PR(a_3)={r_1, r_3}. The weights on goals are assumed to be w(g_1)=2, w(g_2)=1. From the information requirements and weights on goals, each information requirement is assigned a priority as follows:

$$PRIO(a_0, r_1) = \frac{1}{2} = 0.5$$

$$PRIO(a_0, r_2) = \frac{2}{2} + \frac{1}{2} = 1.5$$

$$PRIO(a_0, r_3) = \frac{2}{2} = 1$$

If agent 0 requests r_1, r_2, r_3 from a_1, a_2, a_3 respectively, goal coverage for each goal and coverage value from the selected provider agents become:

$GoalCoverage(a_0, \{a_2, a_3\}, g_1) = (1.5+1)/(1.5+1) = 1$

$GoalCoverage(a_0, \{a_1, a_2\}, g_2) = (1.5+0.5)/(1.5+0.5) = 1$

$Coverage(a_0, \{a_1, a_2, a_3\}, \{g_1, g_2\})=(1+1)/2=1$

On the other hand, if agent 0 requests r_2, r_3 from a_1, a_2 respectively but does not request r_1, then goal coverage for each goal and coverage value from the selected provider agents become

$GoalCoverage(a_0, \{a_1, a_2\}, g_1) = (1.5+1)/(1.5+1) = 1$

$GoalCoverage(a_0, \{a_2\}, g_2) = (1.5+0.5)/1.5 = 0.75$

$Coverage(a_0, \{a_1, a_2, a_3\}, \{g_1, g_2\})=(1+1)/(1+0.75)=0.875$

If an agent is concerned only about satisfying the information requirements, the objective is to maximize *Coverage*. However, there can be multiple different source combinations which maximize *Coverage*. The choice of information source combination can affect the robustness of the goal achievement. Assume there are 2 instances of source combinations which maximize *Coverage* where one instance consists of a higher number of provider agents (e.g., 3 information elements from 3 provider agents) and another instance of a lower number of provider agents (e.g., 3 information elements from 1 provider agent). If an agent prefers the first case – more provider agents – the agent is less dependent on the undesirable (as well as desirable) behavior of those provider agents. On the other hand, if an agent prefers the second case – less provider agents – the agent is more dependent on the undesirable (as well as desirable) behavior of those information sources. The decision of which information source combination to choose in those cases is a design consideration of agent designers.

3.3.1.2 Cost

When an agent has unlimited resources for the information acquisition process, the agent should pursue the highest quality information possible. However, an agent is often limited by the information costs it can afford; therefore, the agent must address the quality and efficiency tradeoffs between acquiring quality information at a reasonable cost [Park and Barber 2004].

Information cost is derived from the message-passing and computational burden required to communicate information. In many information networks, such as ad-hoc networks, agents are not connected to every source. As a result, information must pass through other providers (providers willing to relay information) to arrive at the requesting agent, and consequently information cost is increased. In this research it is assumed, for simplicity, that information cost is directly proportional to the number of messages each agent needs to handle. As a consumer agent with N information requirements, the minimum number of messages including requests and replies in each round is 2N in a partner selection problem because each provider is willing to provide requested information. The cost of information acquisition plays a significant role for selecting provider agents if the willingness of information supply is not assumed as in the collaboration problem in the next chapter. If provider agents are not willing to provide the requested information but can choose whether to provide or not, a consumer agent may need to request information multiple times causing a cost increase. Although cost is defined as a message complexity in this research, it should be noted that other information cost such as the hop-by-hop message delivery cost or the real cost of information when the information is not free can be incorporated into cost calculations.

3.3.1.3 Trustworthiness

The trustworthiness of an information provider agent can be represented by the probability that the provided information is true, or the probability distribution of the error of the provided information from the true value [Fullam and Barber 2004]. However, it is not always possible to know the true value of provided information. Thus, a statistical modeling of provided information and providers [Fullam and Barber 2004] is extended to estimate the true value and errors of the information, although we do not limit our trustworthiness evaluation to a specific evaluation mechanism for generality.

In Fullam and Barber [2004], a belief revision algorithm based on a set of policies for information valuation is proposed. Belief is an agent's perspective model of truth, or something believed as true, on some subject at some time. The policies include the preference to the information from the reliable sources with high certainty in information quality, as well as the preference for agreed-upon information from as many sources as possible. The source reliability model is for trustworthiness evaluation in this research. In this model, belief distribution mean μ_B and belief distribution standard deviation σ_B are used to represent a belief. Source distribution is a distribution of source reports represented by source distribution mean μ_{s_i} and source distribution standard deviation σ_{s_i}. The trustworthiness of an information source (called reputation or reliability in Fullam and Barber [2004]) is modeled as a distribution of source report errors. Since the reliability of information source concerns the errors of the reported information and the agent does not know the truth value of the information, the distribution ρ_{s_i} of the source report errors use the mean difference α between the reported values and the belief of the agent. Therefore, the distribution ρ_{s_i} after N timestep is represented by its mean μ_{ρ,s_i} and standard deviation σ_{ρ,s_i}.

$$\mu_{\rho,s_i} = \frac{\sum_{t=1}^{N}\left(\frac{1}{\sigma_B(t)\sigma_{s_i}(t)}\alpha(t)\right)}{\sum_{t=1}^{N}\left(\frac{1}{\sigma_B(t)\sigma_{s_i}(t)}\right)}$$

$$\sigma_{\rho,s_i} = \sqrt{\frac{\sum_{t=1}^{N}\left(\frac{1}{\sigma_B(t)\sigma_{s_i}(t)}(\mu_{\rho,s_i}-\alpha(t))^2\right)}{\sum_{t=1}^{N}\left(\frac{1}{\sigma_B(t)\sigma_{s_i}(t)}\right)}}$$

where $\alpha(t) = \mu_{s_i}(t) - \mu_B(t)$. Since the mean value describes the accuracy and the standard deviation describes the consistency of the information source, we define the trustworthiness of a provider agent s as a linear combination of those two values as:

$$Trust(a_i, s) = \frac{1}{1+e^{B(\xi|\mu_{\rho,s}|+(1-\xi)\sigma_{\rho,s}-z)}}, \text{ where } 0 \le \xi \le 1$$

The weight factor ξ is decided depending on whether an agent a values accuracy or consistency. *B* is the growth rate and z is a domain-specific bias parameter. Depending on the domain-specific bias parameter, an agent can take an optimistic or pessimistic trustworthiness evaluation approach. When an agent evaluates the trustworthiness of multiple sources, it is reasonable to take an average of the selected sources.

Given three evaluation parameters, a combined metric for a set of provider selection for respective information requirements is defined as follows:

$$E(a_i, S) = \frac{Coverage(a_i, S)}{\sum Cost} \cdot \frac{\sum Trust(a_i, S)}{|S|}$$

Ideally, the best information provider combination yields the information supply with maximum quality and coverage, and minimum cost as in point ***p*** in Figure 6.

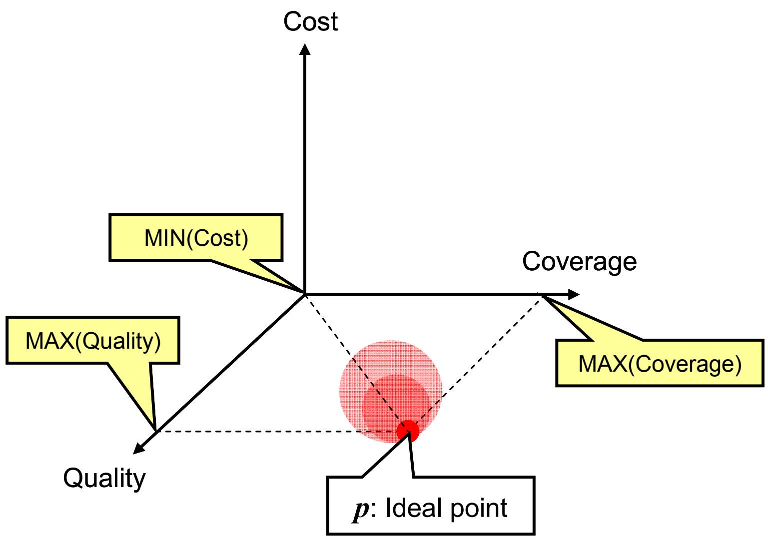

Figure 6 Ideal Partner Selection

In practice, the objective of a consumer agent is to decide a set of provider agents S such that the combined reward or utility is maximized by considering the tradeoffs among those three metrics, $S = \arg\max_{S'} E(a_i, S')$.

3.3.2 Selecting Information Providers

The ultimate objective of an information consumer agent is to select a set of information providers which maximize the information acquisition utility. However, from an AI planning perspective [Sacerdoti 1975; Korf 1987; Selman, Levesque *et al.* 1992; Park and Barber 2005a], it is often essential for an agent to satisfy the information requirements when there are available information providers. Therefore, the maximization of the information acquisition utility function is pursued in two different ways in this dissertation. First, when an information consumer agent is able to satisfy the information requirements from other information providers, an information consumer agent pursues the maximization of the coverage first, even if the highest quality or the lowest cost cannot be guaranteed, and then tries to maximize the rest of the evaluation metrics. In other words, an information consumer agent compares the trustworthiness and cost of the information providers who can together satisfy the information requirements. This approach often helps reduce the complexity of selecting the solution by pruning out the unnecessary solutions while guaranteeing the acquisition of all the required information. Second, when an information consumer agent is not able to satisfy the information requirements from other information providers, the information consumer agent pursues the maximization of the proposed utility. Depending on the agent designer's objective, each metric can be weighted in a different way, but still the objective is to maximize the coverage and quality while minimizing the cost in a given situation.

3.3.3 Search

When a single information provider per information requirement is assumed, the consumer agent may pursue the optimal information providers based on the defined evaluation metrics. However, when multiple information providers can be selected per information requirement (which is often the case in belief revision processes), selecting the best set of information providers may be intractable because of the explosion of the search space size. This section provides heuristic search techniques for selecting "good-enough" partners in the presence of computational bounds.

3.3.3.1 Search Space Construction: Information Source Combinations Pool

The partner selection process aims to select the best information providers which maximize the reward function $E(a_i, S)$. The naïve approach to finding the best information sources is to investigate every possible combination of information providers which satisfies an agent's information requirements for its goals and pick the one which yields the highest expected reward value. The first phase for the proposed partner selection process is to build a search space, which consists of a set of nodes representing potential information source combinations. Since each instance of information source combination $\{S(a_i, r_k)\}$ constitutes a node in a search space, we use a simple notation to represent an instance of information source combination. A node in a search space is represented by M-tuple which uses the index of element in the tuple as the index of information requirement. Therefore, the M-tuple is constructed as follows:

$$< S(a_i, r_1), \ldots, S(a_i, r_M) >: \text{a node in a search space}$$

The search space is constructed as a graph called the Information Source Combinations Pool (ICP). In the graph, $< S(a_i, r_1), \ldots, S(a_i, r_M) >$ is a node and there exists an edge between two nodes where a single information source addition for a single information requirement can be mapped into the other connected node. For example, there is an edge between $<\{a_2, a_4\}, \{a_2, a_3\}, \{a_3, a_4\}>$ and $<\{a_2\}, \{a_2, a_3\}, \{a_3, a_4\}>$, because $<\{a_2, a_4\}, \{a_2, a_3\}, \{a_3, a_4\}>$ can be made by adding a source a_4 for r_1 to $<\{a_2\}, \{a_2, a_3\}, \{a_3, a_4\}>$ (Figure 7).

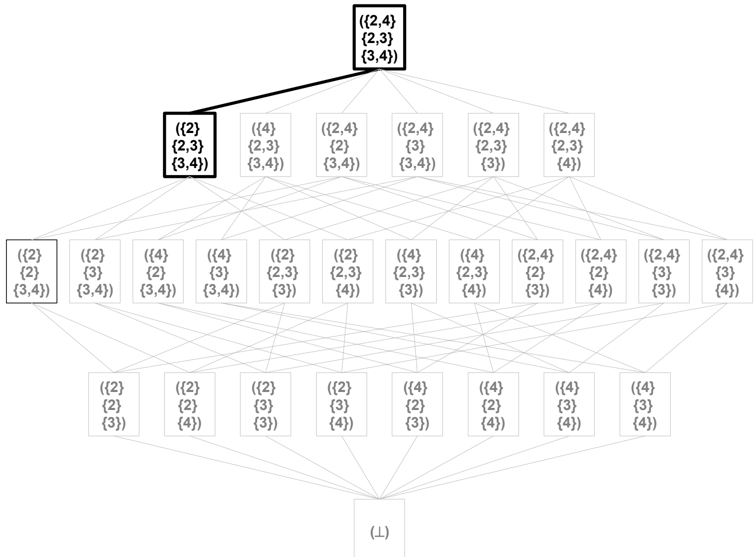

Figure 7 Partial Construction of Information Source Combination Pool

For each information requirement, r_k, an agent a_i can select at least one to at most $|S(a_i,r_k)|$ sources. Also, for different numbers of sources, multiple combinations are possible, so for a single information requirement r_k, the number of possible combinations becomes $\sum_{j=1}^{|S(a,r_k)|} {}_{|S(a,r_k)|}C_j$. In the search space, there are $\prod_{k=1}^{M}\left(\sum_{j=1}^{|S(a,r_k)|} {}_{|S(a,r_k)|}C_j\right)$ nodes with M information requirements, and it is necessary to compare all the nodes to select the best node, which is the best combination of information sources. However, the search space is extremely large as the number of information requirements increases, or the number of sources for each information element increases. Therefore, instead of exploring the whole search space, this research provides a heuristic search technique (Hill-Climbing with Mutation Operation), which is a modified version of hill climbing, and incrementally improves the search result at each timestep.

The implication of the edge between the nodes of a single source change in the ICP is to let an agent make use of the locality of the search space while making it easier to expand the exploration of search space. The currently selected partners are supposed to be the best sources combination up to the current timestep, and the partners are replaced by new partners when the new partners are proved to (1) include more better partners, (2) exclude bad partners from the current partners or (3) be an almost or completely new set of information sources having a higher evaluation value than the current ones. In the case of (1) and (2), it is likely that large parts of the current partners are still included. Therefore, it is desirable to keep the search path near the current node because it is more likely that a better node exists near the current node. By harnessing this locality, a search can be efficiently performed. However, depending only on the locality, it can reach a local optimum or slow down the search in the case of (3), so we need to expand the exploration of the search space to reduce the possibility of the local optimum. Expanding the exploration in turn costs more and may waste the resource if the exploration does not return a better result. The hill-climbing with mutation operation concurrently takes care of both the exploitation, by adopting a hill-climbing search method, and the exploration by adopting a mutation operation borrowed from genetic algorithms. Before we discuss the search algorithm in detail, we will give an illustration of search space construction with an example.

The following example is used to describe the approach:

$$A = \{a_1, a_2, a_3, a_4\},\ RQ(a_1) = \{r_1, r_2, r_3\},\ S(a_1) = \{a_2, a_3, a_4\}$$
$$PR(a_2) = \{r_1, r_2\}$$
$$PR(a_3) = \{r_2, r_3\}$$
$$PR(a_4) = \{r_3, r_1\}$$

Then, an Information Source Combination Pool (ICP) can be built as in Figure 8 with 27 source combinations.

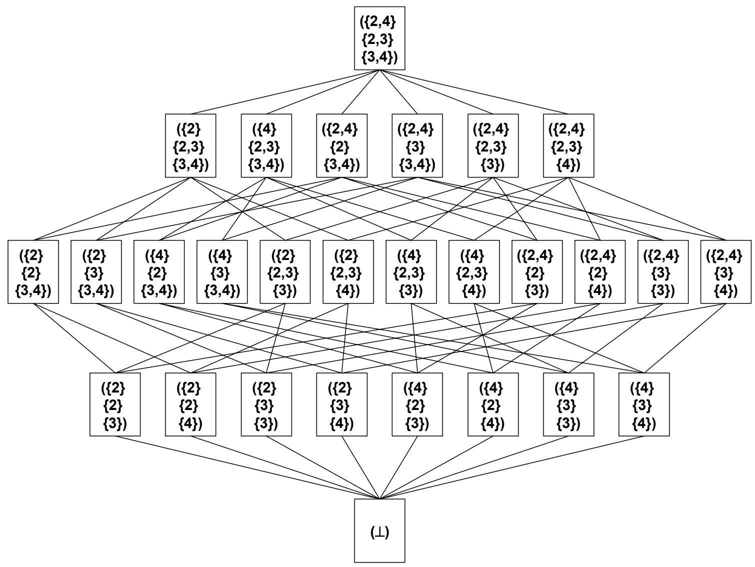

Figure 8 Information Source Combination Pool (ICP)

In this figure, the root node is a node which contains all the sources for all the requirements, and the bottom node is an unreachable empty source combination. We can see there is an edge between two nodes where a single information source addition for a single information requirement can be mapped into another connected node. Although, this graph shows the whole structure of the nodes and edges, an agent does not build the whole space but rather expands the connected nodes from the current node when it is necessary.

3.3.3.2 Search Algorithms

We deploy a hill-climbing search algorithm [Rich and Knight 1991] and a mutation operation from a genetic algorithm [Holland 1975]. Hill-climbing is a heuristic search to head towards a state which is better than the current state. Therefore, we can always get a result which is better than or at least equal to the current state. However, the problem is that the hill-climbing can fall in a local optimum. Mutation operation helps reduce the possibility of a local optimum problem. Mutation serves to generate a new node to be inspected by applying a simple modification rule to the current node, and enables random walks in the search to detect a local optimum and helps escape from the local optimum.

3.3.3.2.1 Hill Climbing

The hill-climbing search method is applied to the Information Source Combinations Pool (ICP) to find the best information source combination. The initial node can be set to be either a root node in the ICP or a random node. Each time, agent a_i executes *PartnerSelection*(a_i) to compare the currently selected information sources ($S_{sel}(a_i)$) with the connected nodes ($\{S(a_i)\}$). If there is a node which is evaluated to be a better source combination than the current one, a_i switches to the new partners. Therefore, a_i can select an information source combination which is better than or equal to the current one. Since only the current node and the connected nodes are inspected, an agent does not need to build the whole ICP graph. Algorithm 1 illustrates the algorithm details.

```
PartnerSelection(a_i):
        S_sel(a_i) = current partners
        for connected nodes {S(a_i)} of S_sel(a_i) in ICP
                if E(a_i, S(a_i)) > E(a_i, S_sel(a_i))
                        S_sel(a_i) = S(a_i)
                end if
        end for
```

Algorithm 1 Hill-Climbing Search in Information Source Combination Pool

3.3.3.2.2 Hill Climbing with Mutation Operation

The hill-climbing method can confront a local optimum. In order to escape from the local optimum, it is necessary to observe additional nodes which are reasonably far away from the current node. However, there are tradeoffs in adding more nodes for comparison. Additional nodes can either contribute to escaping from the local optimum or waste an agent's computation resources.

A mutation operation found in genetic algorithms [Holland 1975] can help prevent a local optimum by randomly changing a part of the results. The mutation operation is diverse and very dependent on the encoding scheme of the elements in a search space. The most popular mutation operator involves bit inversions in binary encoding. The bit inversion in binary encoding will randomly switch a few chosen bits from 1 to 0 or 0 to 1. For example, if a node is represented as 10010011 in binary, possible results of mutation are 11010011 or 10100011. 11010011 is a switch of the second bit from 0 to 1, and 10100011 is a switch of the third and the fourth bits from 0 to 1 and 1 to 0. In this research, a node in the ICP is encoded as $< S(a_i, r_1), ..., S(a_i, r_M) >$ representing the selected information sources for a corresponding information requirement. Thus, this research will derive reasonable mutation operations which help circumvent a local optimum. In Algorithm 2, we show how mutation can be added to the hill-climbing search algorithm.

The idea is to inspect mutated nodes after selecting a set of information sources. If there is an information source combination in a set of mutated nodes which is better than the selected information sources, an agent takes the newly found combination as the best information source combination. $S_{mutation}(a_i, S_{sel}(a_i))$ represents an information source combination which is mutated from $S_{sel}(a_i)$, which results from applying MUTATION operation on $S_{sel}(a_i)$.

PartnerSelection(a_i):

$S_{sel}(a_i)$ = current partners

for connected nodes $\{S(a_i)\}$ of $S_{sel}(a_i)$ in ICP

if $E(a_i, S(a_i)) > E(a_i, S_{sel}(a_i))$

$S_{sel}(a_i) = S(a_i)$

end if

end for

$\{S_{mutation}(a_i, S_{sel}(a_i))\}$ = MUTATION ($S_{sel}(a_i)$)

for all $S_{mutation}(a_i, S_{sel}(a_i))$

if $E(a_i, S_{mutation}(a_i, S(a_i))) > E(a_i, S_{sel}(a_i))$

$S_{sel}(a_i) = S_{mutation}(a_i, S(a_i))$

end if

end for

Algorithm 2 Hill-Climbing Search with Mutation Operation in ICP

MUTATION ($S_{sel}(a_i)$):

SourceInversion ($S_{sel}(a_i)$)

for k such that $1 \le k \le M$

return $S'_{sel}(a_i, r_k) = S_{sel}(a_i, r_k) - r_i + r_j$

$, where\ r_i \in S_{sel}(a_i, r_k), r_j \notin S_{sel}(a_i, r_k) \wedge r_j \in S(a_i, r_k)$

end for

ComplementaryInversion ($S_{sel}(a_i)$)

for $\forall k, \overline{S_{sel}}(a_i, r_k) = S(a_i, r_k) - S_{sel}(a_i, r_k)$

return $S'_{sel}(a_i, r_k) = \begin{cases} \overline{S_{sel}}(a_i, r_k),\ if\ \overline{S_{sel}}(a_i, r_k) \neq \varnothing \\ \text{any one source from } S(a_i, r_k) \end{cases}$

end for

RandomMutation ($S_{sel}(a_i)$)

return random $S'_{sel}(a_i, r_k) \notin$ connected nodes of $S_{sel}(a_i, r_k)$.

Algorithm 3 Mutation Operations

Three different schemes for the MUTATION operator are proposed. The first one is the source inversion. Source inversion is inspired by the bit-inversion in binary encoding. The idea is to substitute new sources from the non-selected sources with part of the currently selected sources, where non-selected sources are the potential sources that were not included in the currently selected sources. The second option is the complementary inversion, which is an extension of the source inversion. The complementary inversion seeks to replace the selected sources for each requirement with the new non-selected sources for respective requirements. When the non-selected sources are empty, one source is randomly chosen from potential sources. The last option is the random mutation. Random mutation is to change the selected node randomly, so it is equivalent to selecting another node from ICP which is not directly connected with the selected node. These three schemes are summarized in Algorithm 3.

3.4 SUMMARY

This chapter presents the partner selection algorithms. The objective of partner selection schemes is to select the appropriate set of information providers which maximize the information acquisition utility. Information acquisition utility is defined in terms of coverage, trustworthiness, and cost. Given a set of information providers for information requirements, the coverage of selected information providers represents how much of the portion of information requirements can be satisfied. Trustworthiness represents the accuracy and consistency of the information providers, modeled by the error distribution of the providers using statistical methods. The cost of information acquisition can occur from various sources. The message complexity of information acquisition is used to represent the cost in this dissertation. When the objective of an information consumer is to select one information provider per information request, the complexity of finding the optimal solution is not high, but if multiple information providers per information requirement can be selected, the computation complexity of finding the optimal solution increases exponentially as the size of the system and the number of requirements increase. Heuristic search techniques for finding the near-optimal solution given a limited amount of search time are presented. The heuristic search techniques adopt the hill-climbing algorithm and genetic algorithm.

CHAPTER 4

COLLABORATION AMONG AGENTS

4.1 Overview

In the partner selection problem in the previous chapter, decision-making agents are assumed to be information consumers and provider agents are assumed to provide requested information if available. In multi-agent systems where agents can be consumers and providers at the same time (e.g., grid computing [Czajkowski, Fitzgerald et al. 2001; Foster, Kesselman et al. 2001; Smith 2005]) as well as self-interested meaning they are interested in achieving their own goals, the provider agents may not want to waste their own resources by providing requested information to requesters unless the information supply contributes to the providers' own goal achievement in the future. In other words, agents need to be motivated to provide requested information in the way that the information supply is beneficial to those providers.

The potential benefit information providers can expect is the reciprocal supply of necessary information from the requesting agents. A prerequisite condition for establishing this reciprocally beneficial relationship is information interdependence, meaning the agents at both ends are partially or completely complementary about the deficient information requirements and available information for others. However, even with the existence of reciprocal information interdependence it is difficult for agents to figure out the best way to request information and respond to others' requests when there are multiple agents with multiple information elements which need to be provided or are available for supply, because of the additional computational complexity and the effect of other agents' interdependence on the decision of building relationships. In addition, the information requirements can dynamically change over time, depending on the ratio of the information requirements' satisfaction from the previous interaction, or agents may need a completely different set of information to achieve different goals or sub-goals. Therefore, it is necessary for an agent to model the other agents' action selection about information exchange, as well as to figure the best actions based both on the model of other agents and its own dynamic information requirements.

The uncertainty in the quality of provided information can also affect the agents' decision on building relationships with other agents. Agents need to take into account the trade off between the quality of information and the probability of acquiring necessary information in order to maximize goal achievability.

In this chapter, agents' information acquisition utility (i.e., goal achievability) is defined using metrics including coverage, cost, and trustworthiness introduced in the previous chapter, and agents' action spaces are defined in terms of requesting strategy as information consumers and responding strategy as information providers. The objective of the strategies is to enable self-interested agents in the information sharing networks to obtain all the necessary information at the least cost, by building collaborative relationships with complementary and trustworthy agents while avoiding being exploited by selfish agents, using the history of interactions.

4.2 *CoCoAgents*: Competitive Collaborating Agents

The *Competitive Collaborating Agents* (*CoCoAgents*) are self-interested, but need to exchange information with appropriate counterparts. *CoCoAgents*' goals impose a set of information requirements which need to be satisfied along with a set of information available for other agents. Therefore, *CoCoAgents* can act as an information consumer and a provider at the same time, and two types of decisions need to be made:

- Strategy for requesting information: an agent's strategy for requesting determines how effectively the agent receives information elements from other information providers (i.e., other agents). The acquisition of information elements in turn contributes to an agent's overall rewards.
- Strategy for responding to other agents' requests: an agent's strategy for responding to information requests from other agents determines how many requests the agent responds to. The reciprocal sharing of information between agents may ultimately allow a given agent to better acquire needed information elements, which in turn contributes to an agent's overall rewards.

Each type of strategy decision is not independent of the other type. An agent's strategy about how to provide information may affect other agents' strategies for how to request information as well as how to respond to the agent's requests, which can eventually affect the agent's strategy for how to request information. If the decisions about requests and responses are made simultaneously, the space size for strategies can easily become intractable, and an unrealistic assumption about system-wide synchronous message delivery of requests and replies needs to be made for simultaneous decisions. Since each type of strategy contributes to the rewards (payoff) in different ways, separating each type of strategy and determining how different types of strategies are related aids in agents' decision-making process with regard to designing rewards and reducing search space. In the following section, more details of the problem are provided followed by the overview of stochastic game theory which is used as a formal framework for this research.

4.3 Problem Statement

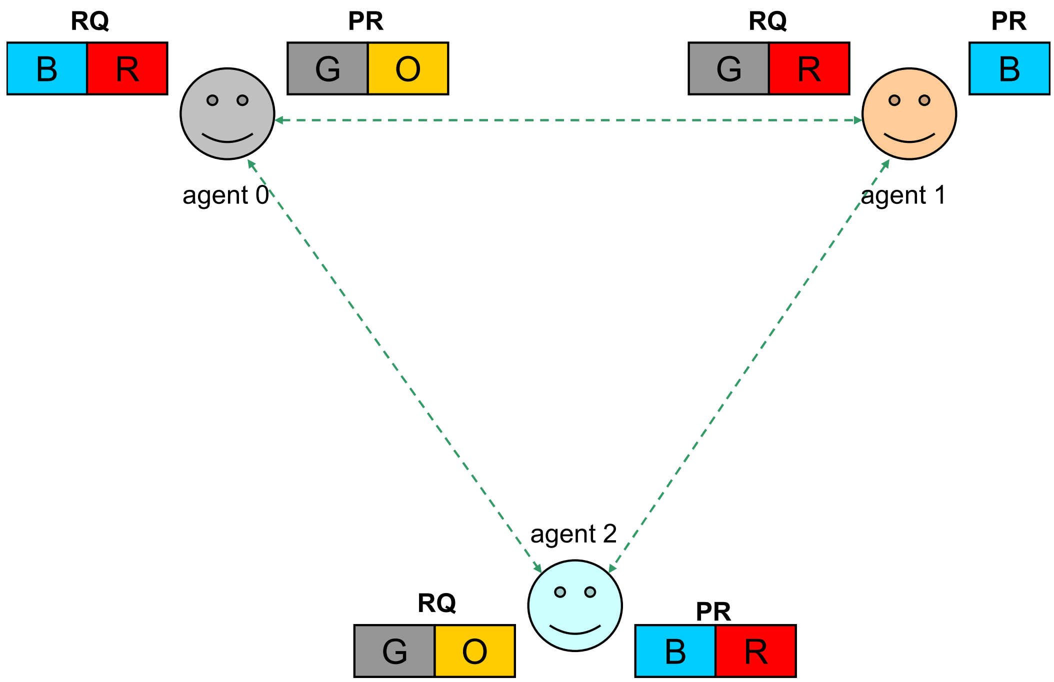

Figure 9 Example Scenario of Information Sharing Networks with Information Requirements and Available Information

CoCoAgents play the role of an information providers and consumers at the same time. *CoCoAgent*s' information requirements (RQ) are a set of required information elements for goal achievement. Each *CoCoAgent* also has a set of available information elements (PR) for others (Figure 9). Agents join the information sharing networks because they are not self-sufficient in terms of information acquisition capability. Therefore, the information requirements, which are deficient information, need to be acquired from external sources (e.g., other provider agents).

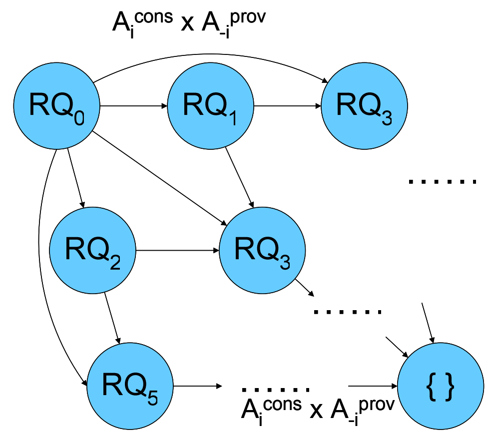

Figure 10 *CoCoAgent*'s Finite State Machine Representation of Information Request Decision Making

CoCoAgents' internal decision-making process about information requests (i.e., selecting the information provider agents) can be represented by a finite state machine as in Figure 10. A *CoCoAgent* has the states of information requirements, and transitions from one state to another state are triggered by a product of an information consumer agent's action and provider agents' actions. Each *CoCoAgent* i has two types of actions defined as follows:

- A_i^{con} (consumer actions): a set of requests for information requirements in the current state.
- A_i^{prov} (provider actions): a set of responses to requested information elements in the current state

Agents in competitive environments do not usually share an internal model with other agents. Thus, the consumer agents do not have access to the quality of provided information (i.e., a provider agent's trustworthiness) and other agents' actions as providers. As a result, the transition between two states is not deterministic because of those uncertainties.

In this situation, the objective of *CoCoAgents* is to determine the best action set (i.e., strategy) for requesting information which maximizes the utility gained to reach the destination state (i.e., empty information requirements).

In order to address the problem, the following section introduces an overview of stochastic game theory and shows how a stochastic game is deployed for *CoCoAgents*.

4.4 MODELING THE DECISION-MAKING PROCESS AS A STOCHASTIC GAME

A stochastic game [Shapley 1953a; Bowling and Veloso 2000; Hu and Wellman 2003] is a tuple (S, A_1, ... ,A_n, u_1, ... , u_n, p), where S is the state space. A_i is the action space for player I, n is the number of players, u_i: $S \times A_1 \times \ldots \times A_n \rightarrow R$ is the reward function of player i. p: $S \times A_1 \times \ldots \times A_n \rightarrow \Delta(S)$ is the transition probability, where $\Delta(S)$ represents the set of probability distribution over S and p satisfies the condition:

$$\sum_{s' \in S} p(s' \mid s, a_1, \ldots, a_n) = 1,\ a_i \in A_i$$

At a state $s \in S$, each agent selects actions a_1, …, a_n, and receives rewards $u_i(s,a_1,\ldots,a_n)$, and makes a transition to $s' \in S$ depending on the transition probability. The objective of each agent is to find an action strategy which maximizes the discounted sum of rewards represented by v_i, where π_i is the action strategy of player i, $\beta \in [0,1)$ is a discount factor, u_i^t is a reward for player i at time t, and s_0 is an initial state.

$$v_i(s, \pi_1, \ldots, \pi_n) = \sum_{t=0}^{\infty} \beta^t E(u_i^t \mid \pi_1, \ldots, \pi_n, s_0 = s)$$

In information sharing networks, each state is represented by the information requirements, and the rewards are defined in terms of the coverage of information requirements [Barber and Park 2003] attained by taking an action for information request and corresponding reception of the necessary information. Each agent's action space consists of two separate spaces: actions for information request as an information consumer and actions for information supply as an information provider. Accordingly, the action space for each agent can be represented by $A_i = A_i^{prov} \times A_i^{cons}$, where A_i^{prov} is the action space consisting of the available actions as an information provider, and A_i^{cons} is the action space with available actions as an information consumer. The joint action space $A = A_1^{prov} \times A_1^{cons} \times \ldots \times A_n^{prov} \times A_n^{cons}$ can be decomposed into 2 terms based on agents' roles and correspondence. From an information consumer's perspective, the actions to be taken into account by agent *i* for calculating rewards are its actions for requesting information and the corresponding actions of other agents as providers (Equation 1). The action space as an information provider (Equation 2) consists of an agent's actions for responding to other agents' requests and corresponding request actions by other agents.

$$A_i^{cons} \times \prod_{j=1, j \neq i}^{n} A_j^{prov}$$

Equation 1 Information Consumer's Actions and Corresponding Actions of Providers

$$A_i^{prov} \times \prod_{j=1, j \neq i}^{n} A_j^{cons}$$

Equation 2 Information Provider's Actions and Corresponding Action of Consumers

The rationale for decomposing the action space into multiple types based on roles is that each dimension contributes to the expected reward in different ways. However, since they are not completely independent, the effect of one action type on the other also needs to be considered. The following sections present detail about modeling action spaces and strategy selection for an information consumer and an information provider.

4.5 APPROACH

This section describes information sharing strategies. The strategy for information consumer agents is presented in the following sub-section, followed by the strategy for information provider agents.

4.5.1 Strategy for Information Consumer Agents

An agent i has a set of information requirements RQ(a_i) = $\{r_k\}$ and a set of available information PR(a_i) = $\{r_p\}$ for other agents and itself. The state of an agent is represented by the information requirements. The action space at a given state is dependent on the current information requirements and the available information providers. The reward from actions at a given state is calculated by the coverage, and the expected reward for reaching the final state (i.e., no more information requirements) is adjusted by the total cost and the trustworthiness of the gathered information; the coverage is the percentage of information requirements satisfied by the actions, the trustworthiness measures the consistency and accuracy of the provided information, and the cost is represented by message complexity (i.e., number of messages). It is assumed that once an agent reaches the final state, the state is reset to the initial state infinitely. In other words, infinite interactions are assumed in the way that there is a transition with no additional rewards or cost from the final state to the initial state.

Available actions for an information consumer are a set of requests to a subset of available information providers. When interacting agents commit actions, the information requirements for an information requester can therefore change, and the requester's state transits to the next state. In the next state, due to the change in information requirements, available action sets are different from the previous state unless the agent stays in the same state with the previous one. Therefore, at each state agents play different games, which make the deployment of a stochastic game the most appropriate for information sharing networks. The strategy for this stochastic game is stationary, and in a stochastic game with stationary strategies there exists at least one Nash Equilibrium point [Nash 1950; Nash 1951], where the strategies in Nash Equilibrium are defined as a tuple of strategies ($\pi_1^*,\ldots, \pi_n^*$) such that for all $s \in S$ and i=1,…,n,

$$v_i(s, \pi_1^*, \ldots, \pi_n^*) \geq v_i(s, \pi_1^*, \ldots, \pi_{i-1}^*, \pi_i, \pi_{i+1}^*, \ldots, \pi_n^*), \forall \pi_i$$

In Nash Equilibrium, each agent cannot be better off by deviating from the current strategy without any change in other agents' strategy [Nash 1950; Nash 1951]. Also, an agent's strategy is the best response to others' strategies in Nash Equilibrium, where the best response is the strategy which results in the most favorable immediate outcome for the current player, given others' strategies.

This research experimentally shows how agents reach the equilibrium by finding the best response given the action spaces, reward structure, and observations about other agents.

Agent i's consumer action $a_i^{cons}=\{request_i(j,\ r_k)\}$ denotes that agent i requests information element k from agent j. The requests have to satisfy the constraints that all the required information elements are requested and each element can be requested from a single information provider. The strategy of agent *i* for requesting information, $\pi\text{-}in_i$, is a path of actions which maximize the discounted sum of rewards (Equation 3) when the other agents have the strategy $\pi\text{-}out$, for providing information. $\pi\text{-}out_{-i}$ in Equation 3 represents strategies of agents but agent *i* for providing information.

$$v_i(s, \pi\text{-}in_i, \pi\text{-}out_{-i}) = \sum_{t=0}^{\infty} \beta^t E(u_i^t \mid \pi\text{-}in_i, \pi\text{-}out_{-i}, s_0 = s)$$

Equation 3 Discounted Reward Sum

From the information consumer agents' point of view, the information providers' actions for their own requests are recognized as being comprised of either to provide ($provide_j(r_k, i)$) or not to provide the requested information ($\neg provide_j(r_k, i)$). The set of actions by both providers and a consumer lead a static state transition to a certain state with a probability of 1.0, but since the probability of actions being committed by providers can vary depending on the providers' strategy, rewards are scaled by $RR(i, j)$. In other words, expected rewards are obtained by taking into account the coverage for a pair of requesting strategy and responding strategy and the probability of the pair of strategies to actually occur. The trustworthiness of the information elements is also incorporated into the expected rewards. The trustworthiness of an information provider agent is established by building a statistical error model of the information provider agent (see Chapter 3). As a result, for a transition from a state to another state by a consumer's action A_i^{cons} and providers' actions A_{-i}^{prov}, the expected reward can be expressed as in Equation 4.

$$E(u_i \mid A_i^{cons}, A_{-i}^{prov}) = \Delta coverage \cdot \overline{TR}(a_{-i}) \cdot \prod_{-i} \Pr(A_{-i}^{prov})$$

Equation 4 Expected Reward

In Equation 4, $\overline{TR}(a_{-i})$ is the average trustworthiness of the selected providers, and $\prod_{-i} \Pr(A_{-i}^{prov})$ is the product of the probabilities each provider commits a provider action as a response to a consumer's action A_i^{cons}. In a competitive environment, it is not assumed that an agent knows the exact model of other agents' actions and the selection of the best response. Thus, an agent maintains an estimated probabilistic model of other agents' actions by observation. The *reception rate*, *RR(i, j)* ($\in[0,1]$), is the probability of *j* replying to *i*'s requests and can be calculated by counting the number of requests replied by agent *j*.

In order to take into account the cost incurred during the interactions, discounted reward sum v_i is scaled by the total cost. Therefore, the objective function a consumer agent needs to maximize becomes as in Equation 5, where $cost(\pi\text{-}in_i, \pi\text{-}out_{-i})$ is the cost of agent *i* for the strategy $\pi\text{-}in_i$, $\pi\text{-}out_{-i}$.

$$\overline{v_i}(s, \pi\text{-}in_i, \pi\text{-}out_{-i}) = \frac{\sum_{t=0}^{\infty} \beta^t E(u_i^t \mid \pi\text{-}in_i, \pi\text{-}out_{-i}, s_0 = s)}{\sum cost(\pi\text{-}in_i, \pi\text{-}out_{-i})}$$

Equation 5 Discounted Reward Sum with Cost

The opponent modeling Q-learning method [Uther and Veloso 2003] takes a similar approach for building a model of other agents' actions and calculating the expected rewards. The opponent modeling Q-learning constructs a table of probabilities that other agents take certain actions at a given state and the expected rewards are scaled by the probability so that an agent can calculate the best action.

Figure 11 shows an example of agent 0's state transition graph as a stochastic game. Agent 0 has a set of information requirements RQ(a_0)={r_1, r_2, r_3}.

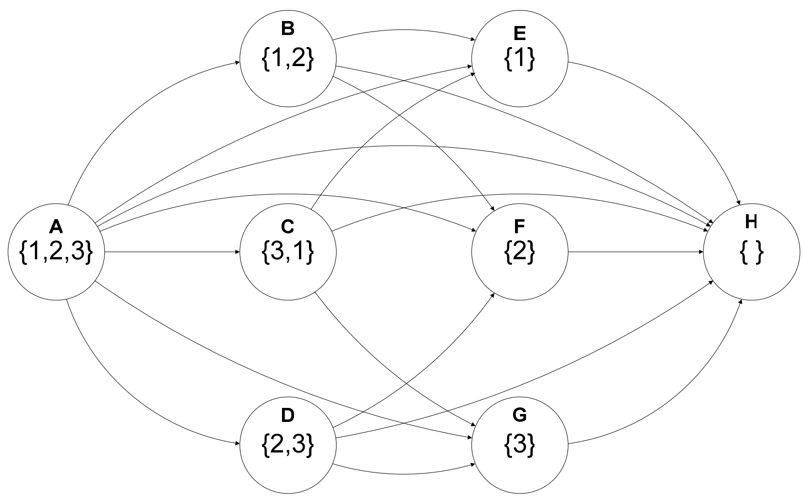

Figure 11 *CoCoAgent*'s Stochastic Game Modeling of Consumer Strategy with Information Requirement {r_1, r_2, r_3}

There are 8 states, including the initial and final state. There can be a loop to each state but the loops are pruned to reduce the computational complexity, because loops to each state do not contribute to expected rewards with no coverage increase. A state transition to another state can be triggered by different combinations of consumer actions and provider actions. For example, assuming each information element from RQ(a_0) can be provided by 2 different provider agents, 8 different combinations of consumer and provider actions can cause a transition from state A to state B. Supposing that there are 3 other agents – agent 1, agent 2, and agent 3 – which can provide the required information

PR(a_1)={r_1, r_2}, PR(a_2)={r_2, r_3}, PR(a_3)={r_1, r_3}, the available actions for agent 0 ($A_{i,j}^{cons}$, where j is an index of an action) at the initial state A are:

$$A_{0,0}^{cons} = \{request_0(1,r_1), request_0(2,r_2), request_0(3,r_3)\}$$
$$A_{0,1}^{cons} = \{request_0(1,r_1), request_0(2,r_2), request_0(2,r_3)\}$$
$$A_{0,2}^{cons} = \{request_0(1,r_1), request_0(1,r_2), request_0(3,r_3)\}$$
$$A_{0,3}^{cons} = \{request_0(1,r_1), request_0(1,r_2), request_0(2,r_3)\}$$
$$A_{0,4}^{cons} = \{request_0(3,r_1), request_0(2,r_2), request_0(3,r_3)\}$$
$$A_{0,5}^{cons} = \{request_0(3,r_1), request_0(2,r_2), request_0(2,r_3)\}$$
$$A_{0,6}^{cons} = \{request_0(3,r_1), request_0(1,r_2), request_0(3,r_3)\}$$
$$A_{0,7}^{cons} = \{request_0(3,r_1), request_0(1,r_2), request_0(2,r_3)\}$$

For $A_{0,0}^{cons}$ at state A, the other agents' actions A_{-0}^{prov} = {$\neg provide_1(r_1,\ 0)$, $\neg provide_2(r_2,\ 0)$, $provide_3(r_3,\ 0)$} lead agent 0 to state B. The reward for the action set $A_{0,0}^{cons}$ and A_{-0}^{prov} at state A without cost factor becomes

$$\begin{aligned}
&E_{A-B}(u_0 \mid A_{0,0}^{cons}, A_{-0}^{prov}) \\
&= \Delta coverage \cdot \overline{TR}(a_{-0}) \cdot \prod_{-0} \Pr(A_{-0}^{prov}) \\
&= 0.33 \cdot TR(a_3) \cdot \Pr(provide_3(r_3,0)) \cdot \Pr(\neg provide_2(r_1,0)) \cdot \Pr(\neg provide_1(r_2,0)) \\
&= 0.33 \cdot TR(a_3) \cdot \Pr(provide_3(r_3,0)) \cdot (1-\Pr(provide_2(r_1,0))) \cdot (1-\Pr(provide_1(r_2,0)))
\end{aligned}$$

At state B, agent 0's possible actions A_0^{cons} are as follows:

$$A_{0,0}^{cons} = \{request_0(1,r_1), request_0(2,r_2)\}$$
$$A_{0,1}^{cons} = \{request_0(1,r_1), request_0(1,r_2)\}$$
$$A_{0,2}^{cons} = \{request_0(3,r_1), request_0(2,r_2)\}$$
$$A_{0,3}^{cons} = \{request_0(3,r_1), request_0(1,r_2)\}$$

If corresponding responses for $A_{0,0}^{cons}$ from provider agents are A_{-0}^{prov} = $\{provide_1(r_1, 0), provide_2(r_2, 0)\}$, the next state of state B is H which is the final state satisfying the information requirements of agent 0. Accordingly, the reward for the action set $A_{0,0}^{cons}$ and A_{-0}^{prov} at state B becomes

$$
\begin{aligned}
& E_{B-H}(u_0 \mid A_{0,0}^{cons}, A_{-0}^{prov}) \\
& = \Delta coverage \cdot \overline{TR}(a_{-0}) \cdot \prod_{-0} \Pr(A_{-0}^{prov}) \\
& = 0.67 \cdot \frac{TR(a_1) + TR(a_2)}{2} \cdot \Pr(provide_1(r_1, 0)) \cdot \Pr(provide_2(r_2, 0))
\end{aligned}
$$

As a result, the discounted reward sum for the above actions yielding transitions from A to B and B to H is:

$$v_0 = E_{A-B} + \beta E_{B-H}$$

, and the scaled discounted reward sum is:

$$\overline{v_0} = (E_{A-B} + \beta E_{B-H}) \Big/ \sum cost$$

Agent 0's objective is to find the strategy for requesting information such that the scaled discounted reward sum is maximized among all possible combinations of actions for all possible paths from the initial (or current) state to the final state. Formally, agent 0's best strategy for requesting information is decide by finding π^*-in_0 such that:

$$\pi^* - in_0 = \underset{\pi - in_0}{\arg\max}\, \overline{v_0}(s, \pi - in_0, \pi - out_{-0})$$

4.5.2 Strategy for Information Provider Agents

CoCoAgents maintain the *degree of collaboration* for making decision on the actions as provider agents.

The strategy of the information provider agents, denoted by *π-out*, indirectly affects the expected rewards by potentially affecting the other agents' responses, thus the expected rewards. Therefore, the information provider agents' strategy aims to adjust the *degree of collaboration* with other agents so that collaborative relationships can be built among the complementary and trustworthy agents. The collaborative relationships by adapting the *degree of collaboration* can help *CoCoAgents* avoid both (1) being exploited by other agents and (2) being isolated from other agents when the agents still need other agents' help. The *degree of collaboration* carries the agent's amount of intention for collaboration with each agent. *CoCoAgent i*'s degree of collaboration with agent *j* is denoted by ***doc(i, j)*** and is modeled as a probability distribution of responses to requests from other agents. Therefore, *CoCoAgents* as information providers make stochastic decisions about whether to reply or not according to the *degree of collaboration*.

The *reception rate* (RR) is an estimated model of other agents' degree of collaboration. *CoCoAgents* build the *reception rate* model based on the observed actions of the interacting agents, and use the *reception rate* as the factor for determining the value of their own degree of collaboration with other agents. Algorithm 4 shows the algorithm for an adaptive degree of collaboration (***adoc***).

CoCoAgent a_i ::

constants:

α: incremental coefficient

δ: decay rate

$doc^{\max}$: maximum degree of collaboration (1.0)

variables:

$doc_t(i,j)$: agent *i*'s degree of collaboration with agent *j* at timestep *t*

$RR_t(i,j)$: agent *i*'s model of reception rate from agent *j* at timestep *t*

$\Delta RR(i,j)$: $RR_t(i,j) - RR_{t-1}(i,j)$

$adaptiveDegreeOfCollaboration(a_i)$:

if $\Delta RR(i,j) > 0$ then

$doc_t(i,j) = doc_{t-1}(i,j) + \alpha \cdot doc_{t-1}(i,j) \cdot (doc^{\max} - doc_{t-1}(i,j))$

elseif $\Delta RR(i,j) < 0$ then

$doc_t(i,j) = doc_{t-1}(i,j) - \alpha \cdot doc_{t-1}(i,j) \cdot (doc^{\max} - doc_{t-1}(i,j))$

elseif $\Delta RR(i,j) = 0$ then

$doc_t(i,j) = \delta doc_{t-1}(i,j)$

Algorithm 4 Adaptive Degree of Collaboration

The degree of collaboration with a provider agent is updated at each timestep. The direction of change in ***doc*** is determined based on the change of the *reception rate* (*ΔRR*). If the reception rate from a provider agent has increased from the previous timestep (*ΔRR*>0), the degree of collaboration with the provider also increases. On the other hand, if the reception rate from a provider agent has decreased from the previous step (*ΔRR*<0), the degree of collaboration with the provider decreases. The amount of change in ***doc*** is determined based on the previous ***doc*** and the incremental coefficient α. The amount of change is a second order polynomial function of the previous degree of collaboration

($\boldsymbol{doc_{t-1}}$), and has the maximum value 0.25α when $\boldsymbol{doc_{t-1}}$ is the center value (0.5) between the maximum (1.0) and minimum (0.0) value (Figure 12). The amount of change as the second order polynomial function aids the convergence of the *degree of collaboration* and prevents any significant fluctuation. The *degree of collaboration* near 0.5 can generally be considered as containing the highest uncertainty.

According to Figure 12, the amount of change in *CoCoAgent*'s *degree of collaboration* is relatively high when the previous degree of collaboration is close to 0.5, accelerating the escape from the most uncertain state. On the other hand, because of the relatively small amount of change near the maximum or minimum value, it takes more iteration of counteractions for *CoCoAgent* to change the relationships. For example, the *degree of collaboration* near 0.5 can quickly converge to either close to the maximum or minimum value, while the *degree of collaboration* near maximum does not easily diverge to the other end (i.e., minimum ***doc***) without a series of decreases in the *reception rate*. In other words, the proposed algorithm for adapting the *degree of collaboration* leverages the construction of collaborative relations or non-collaborative relations by accelerating the change of ***doc*** near unstable relationships (i.e., ***doc*** is near 0.5) and decelerating the change of ***doc*** in relatively stable relationships (i.e., ***doc*** is near 1.0 or 0.0).

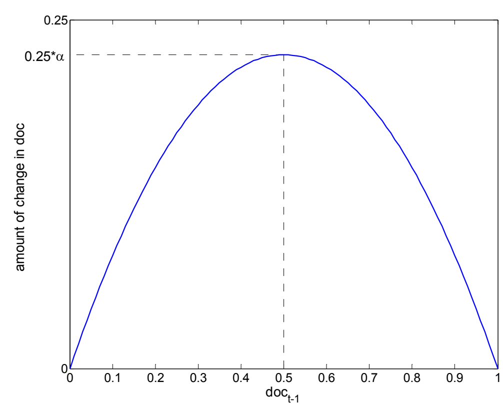

Figure 12 Incremental Value for Degree of Collaboration

Since the *reception rate* can be updated by making information requests and counting the number of replied requests, the *reception rate* does not change (i.e., $\Delta RR=0$) if there have been no requests made in the previous timestep. Keeping the *degree of collaboration* with the non-interacting agents as the same value can let *CoCoAgents* confront the possibility of being exploited by other agents. In order to prevent *CoCoAgents* from being exploited by providing requested information without requesting information from other agents, the *degree of collaboration* with non-interacting agents is decayed by decay rate δ. Decaying the degree of collaboration with non-interacting agents aids in avoiding the exploitation as well as building strong collaborative relationships with interacting agents. In order to minimize the effect of temporal decay and let the degree of collaboration depend more on direct interaction, the decay rate is assumed to be close to 1.0.

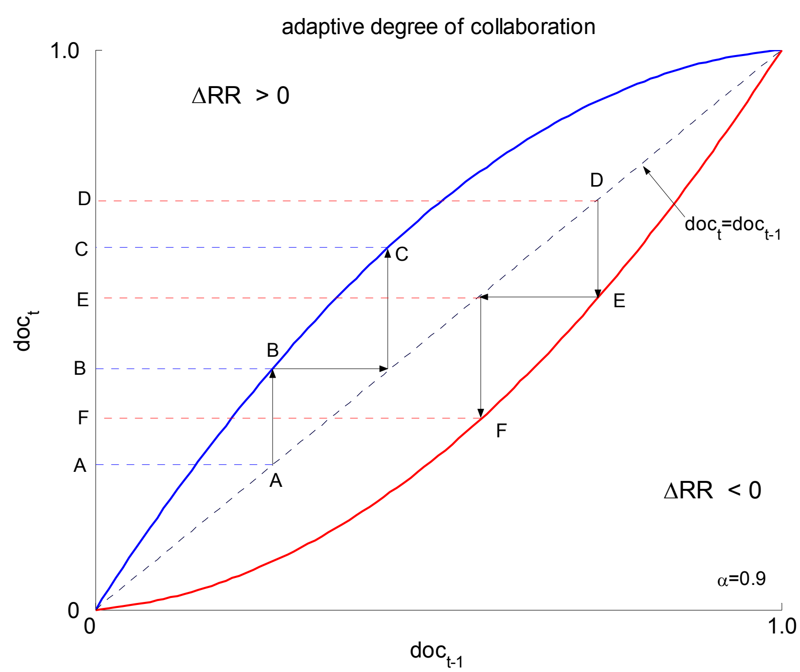

Figure 13 Adaptation of Degree of Collaboration

Figure 13 shows how the *degree of collaboration* changes depending on the previous value when the *reception rate* has been changed from the previous timestep. In the figure, when $\Delta RR>0$, ***doc*** value increases along the curve above $doc_t = doc_{t-1}$. For example, if doc_{t-1} is at point A, an increase of the *reception rate* shifts doc_t to point B. Another increase of the *reception rate* makes the *degree of collaboration* (doc_t) move to point C. In the same way, when $\Delta RR>0$, ***doc*** value decreases along the curve below $doc_t = doc_{t-1}$. For example, if doc_{t-1} is at point D, a decrease of the *reception rate* shifts doc_t to point E, and another increase of the *reception rate* in the next timestep leads the *degree of collaboration* (doc_t) to point F.

4.5.3 Emergence of Collaboration

In game theory, the Prisoner's Dilemma (PD) refers to general-sum games where two players try to receive the higher rewards by choosing an action between *cooperate* and *defect*. In a non-iterated PD, defect by both players is a Nash Equilibrium point though it is not a Pareto-Optimal solution. In the Iterated Prisoner's Dilemma (IPD), Tit-For-Tat [Axlerod 1984] has been the most effective strategy to achieve the maximum rewards. Tit-For-Tat is to cooperate until the opponent defects. When the opponent defects, the player punishes the opponent by selecting *defect*. A Tit-For-Tat strategy is a cooperative approach and the success of the strategy has provided the foundation for the explanation of the emergence of cooperation in human society, in a group of animals, or in politics [Axlerod 1984].

The similarity between Tit-For-Tat and the adaptive degree of collaboration provided in the previous section can be found by investigating a matrix game which can be observed in a state between two agents. Once two agents are assumed to be partially or completely complementary, and both agents request information from each other, the reward matrix for agent 1 (player 1) can be represented as in Table 2. Note that since the requirements and requests change depending on the previous actions, the agents play different games in each state. However, the reward structure observed in each game provides intuition on how collaboration can emerge in information sharing networks.

Table 2 Player 1's Reward Structure

	doc(2,1)=1	**…**	***doc(2,1)=0***
doc(1,2)=1	$\frac{E(u_1)}{cost_c + cost_p}$	…	$\frac{E(u_1)}{cost_c + cost_p} - \frac{E(u_1)}{cost_c}$
…	…	…	…
doc(1,2)=0	$\frac{E(u_1)}{cost_c}$	…	0

As can be seen in Table 2, the game is basically a Prisoner's Dilemma when considering the four extreme cases (***doc*** = *1* and ***doc*** = *0* for each agent). $E(u_1)$ is the expected payoff represented by the product of attained coverage, the probability of achieving the coverage, and the trustworthiness of agent 2. $cost_c$ is the cost of requesting and receiving information, and $cost_p$ is the cost for providing requested information. The difference between traditional PD and the game in the information sharing networks is that the action space for the degree of collaboration is continuous. The adaptation of the degree of collaboration in the previous section is performed in a similar way to Tit-For-Tat. When the opponent has been a collaborative provider (i.e., increasing *RR*), the degree of collaboration is kept higher while the degree of collaboration for the opponent decreases if the opponent tends to be a non-cooperative provider. It is also noteworthy that the degree of collaboration with non-interacting agents decays over time. Among *CoCoAgents*, the emergence of collaboration can be observed because *CoCoAgents* are rational and pursue the reward maximization. Among heterogeneous agents, including *CoCoAgents*, *CoCoAgents* outperform by constructing appropriate relationship with other agents.

4.6 Summary

The objective of each agent is to maximize the information acquisition utility by constructing appropriate relationships with other agents. The agents equipped with information sharing strategies are called *CoCoAgents* (*Competitive Collaborating Agents*). The information sharing strategies for *CoCoAgents* consist of two types of strategies. The first strategy is for the information consumer's role. The strategy as an information consumer is to decide from which information providers to request which information requirements. In order to take into account the previous interaction history and expected rewards in the future, stochastic games are deployed to represent the decision process. In the stochastic game model, the request strategy which maximizes the expected rewards is selected. Expected rewards are calculated using the model of other agents' degree of collaboration, the trustworthiness of the other agents, and the cost of information acquisition.

The strategy as an information provider is to determine the degree of collaboration with other agents. The degree of collaboration is adapted using the model of other agents' degree of collaboration which can be built based on the observations of interactions with other agents. The adaptive degree of collaboration is a variation of Tit-For-Tat from the Iterative Prisoner's Dilemma (IPD) problem in a continuous action space. The adaptive degree of collaboration starts from a high degree of collaboration with others. If an agent detects the decrease of other agents' degree of collaboration, the agent decreases the degree of collaboration with those agents. If an agent detects the increase of other agents' degree of collaboration, the agent increases the degree of collaboration with those agents. If an agent decides not to request information from particular agents (called non-interacting agents), the degree of collaboration with those non-interacting agents decays over time.

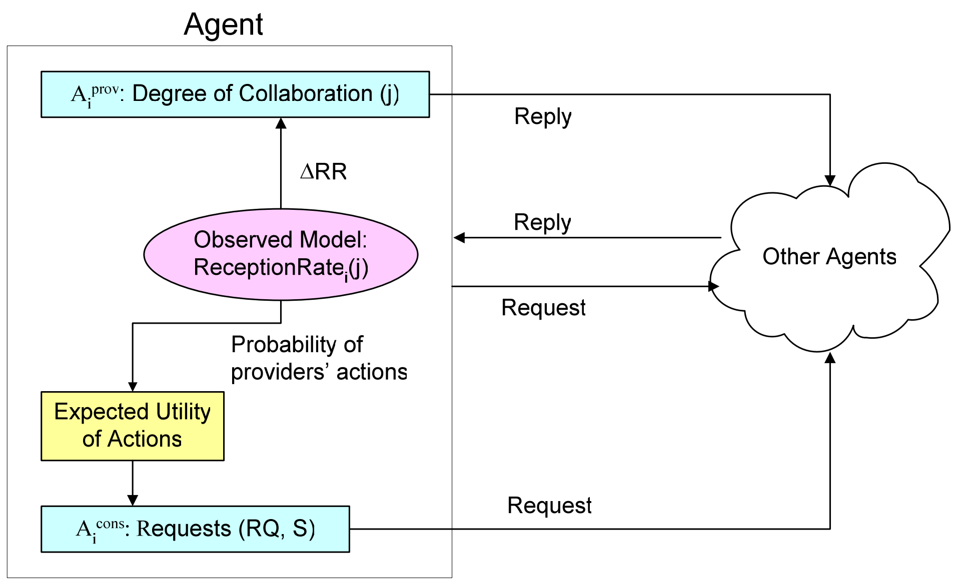

Figure 14 Strategies for Information Providers and Consumers

The overall process for determining information sharing strategies can be depicted as in Figure 14. In the figure, *CoCoAgents* model the other agents' degree of collaboration as *ReceptionRate* by observation, and the *ReceptionRate* affects the adaptation of the degree of collaboration and expected utility of the information request strategy, along with trustworthiness evaluation and cost. The expected utility affects the strategy for information requests. The iterative interactions between agents help to build appropriate relationships among the agents.

CHAPTER 5

EXPERIMENTS

This chapter presents the experimental results to show how the proposed algorithms improve the performance of agents in information sharing networks. Partner selection algorithms are covered in Section 5.1, and the algorithms for collaboration are presented in Section 5.2.

5.1 PARTNER SELECTION

This section presents the experimental results of partner selection algorithms in order to address Research Question 1 (RQ1).

RQ1. How do information consumer agents select the most appropriate information providers so that information acquisition utility can be maximized?

The first set of experiments (Exp 1.1) shows the effect of each evaluation metric on the information acquisition utility. The experiments validate the introduction of each metric by comparing the accomplished information acquisition utility with the utility when each metric is omitted.

The objective of the second set of experiments (Exp 1.2) is to show how the information acquisition utility is affected by the presence of inaccurate information providers. In the experiments, a consumer agent selects a set of providers satisfying its information requirements based on trustworthiness evaluation. The experiment varies the percentage of information providers providing inaccurate information, and compares the quality of acquired information for different schemes.

The third set of experiments (Exp 1.3) aims to show how the information acquisition utility is affected by the amount of effort an agent spends building its trust model of others in the initial stage of interactions. An information consumer is allowed to request information from all available providers for a specified period of time (*trust bootstrap time*) and use the acquired information for building the initial trustworthiness values. Ideally, if an information consumer agent is allowed more time, the consumer agents can gather more evidence, thus build more accurate models of trustworthiness. The experiments (Exp 1.3) investigate how the quality of information and runtime are affected for different *trust bootstrap times.*

The last set of experiments (Exp 1.4 – Exp 1.7) addresses the performance of the proposed heuristic search techniques used to find information providers. Each technique is evaluated in terms of the resulting quality of the acquired information in the presence of inaccurate information providers. Exp 1.4 shows how the quality of information is affected by the time allowed for traversing the search space between each round of information requests. Exp 1.5 and Exp 1.6 take into account the number of information requirements and the number of information providers respectively in the resulting quality of information. Exp 1.7 considers the effect of the number of information providers per each information requirement and the resulting impact on the quality of acquired information.

The following section presents the experimental setups for addressing each question, and shows the results of each experiment.

5.1.1 Experiment Setups and Results

Table 3 shows the experiment setups for Exp 1.1. In the experiments, a consumer agent can select an information provider per its information requirement. In the table,

Number of Providers is the number of information providing agents, and **Number of Requirements** is the number of information elements required by a consumer agent. Each information provider agent is randomly assigned available information elements, and the number of available information elements per each provider is also randomly assigned, but all the information requirements are covered by the union of information providers' available information elements. **Number of Timesteps** is the maximum number of timesteps in each experiment, and **Number of Runs** is the number of experiment runs. **TRUST_BOOTSTRAP_TS** is the number of timesteps allowed for each consumer agent to build its initial trust model of information providers.

During **TRUST_BOOTSTRAP_TS**, an information consumer agent requests information elements from all available providers, and builds its trustworthiness evaluation based on the received information. **Cost Assignment** represents the range of cost values and how the cost of information acquisition is defined. Each provider is randomly assigned a value from [1, 1.2]. Since the cost of a single provider selection per an information requirement does not impose a large amount of cost difference, as opposed to multiple provider selection per information requirement, a small amount of variation ([0, 0.2]) is randomly added to a unit cost (1.0) per information provider. **% Providers with errors** represents the portion of information providers who deliver inaccurate information. Information provider agents providing inaccurate information are randomly selected and provide the information with error mean and error variance proportional to an agent's id (**Error (mean, variance)** in the table). The error mean and error variance values range from [0,1], and the agent with id ***n*** has error (mean, variance) of (***n / Number of Providers***, ***n / Number of Providers***). Therefore, agents with a high id number provide more inaccurate and inconsistent information.

Under the **Cases** parameter, four different schemes are compared with respect to the performance metrics. In each scheme, **TrustEval** represents the use of trustworthiness evaluation based on previous interaction. **FC** represents a full coverage of the information requirements. When a full coverage is guaranteed, the combinations of information providers which can satisfy the information requirements are only included as the potential combinations of information providers. **Cost** represents the consideration of cost factor in the information acquisition utility. Consequently, **TrustEvalFCCost** is a scheme with trustworthiness, coverage, and cost incorporated into the expected reward calculation. **RandomFCCost** guarantees a full coverage of the information requirements and considers cost factor, but trustworthiness evaluation is not conducted. **TrustEvalCost** considers trustworthiness and cost for expected rewards, but does not guarantee the full coverage of the information requirements. **TrustEvalFC** considers only the trustworthiness and guarantees the full coverage of the information requirements.

In **Performance measures**, **MSE** (mean square error) of the received information compared to the true value is used for quality metric, and the **Average Coverage** and **Average Cost** represent the average coverage and average cost at each timestep respectively. **Information Acquisition Utility** represents the accomplished information acquisition utility accumulated over the specified timesteps. Since an information consumer agent selects the information providers based on the *expected* value of the information acquisition utility, the reciprocal value of MSE is used for the calculation of the information acquisition utility instead of the evaluated trustworthiness.

Table 3 Experiment Setups for Exp 1.1

Parameters	Exp 1.1
Number of Providers	30
Number of Requirements per Consumer Agent	10
Number of Timesteps	100
Number of Runs	10
TRUST_BOOTSTRAP_TS	20
Cost Assignment	Random [1, 1.2]
% Providers with errors	100
Error (mean, variance)	(agent id / Number of Providers, agent id / Number of Providers)
Cases	TrustEvalFCCost RandomFCCost TrustEvalCost TrustEvalFC
Performance Measure	MSE Average Coverage Average Cost Information Acquisition Utility

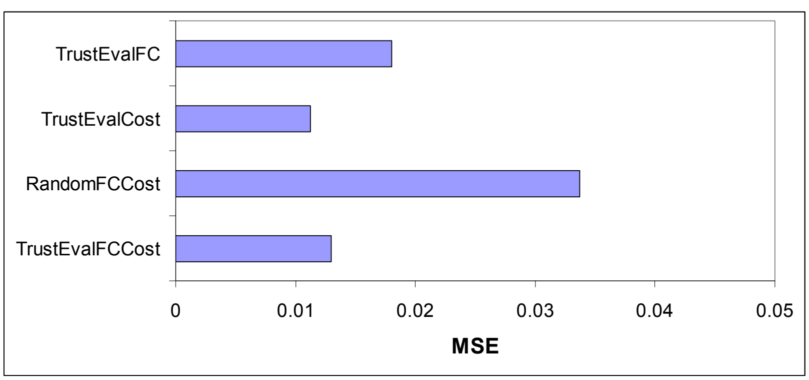

Figure 15 MSE in Exp 1.1

Figure 15 shows the MSE of the received information for each scheme. Without the trustworthiness evaluation (RandomFCCost), higher MSE results while other schemes (TrustEvalFC, TrustEvalCost, TrustEvalFCCost) result in less MSE. The differences between the schemes which use the trustworthiness evaluation are not statistically significant. This experiment explains the necessity of the trustworthiness evaluation for the quality improvement of the received information.

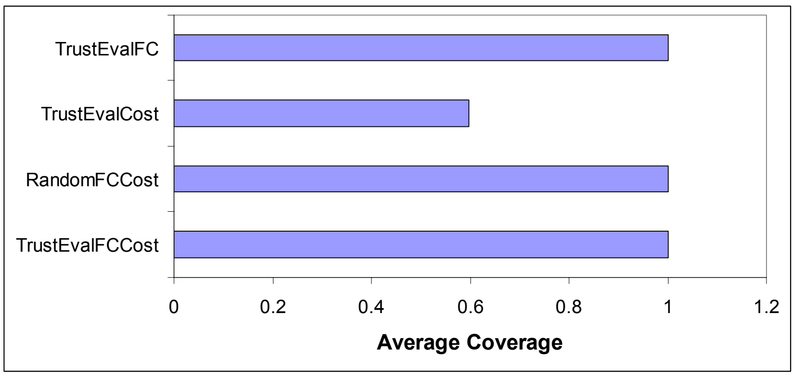

Figure 16 Average Coverage in Exp 1.1

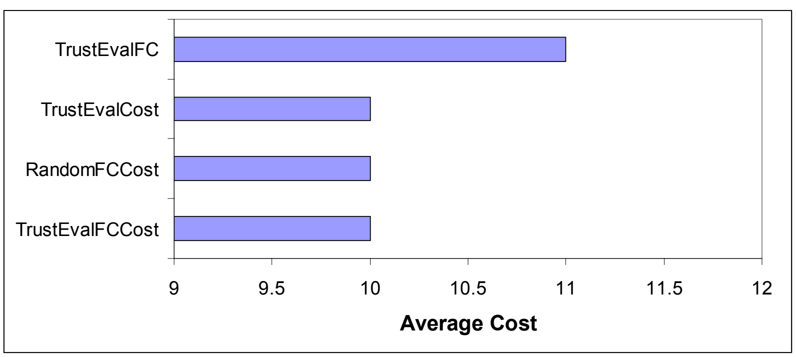

Figure 17 Average Cost in Exp 1.1

Figure 16 and Figure 17 show the effect of incorporating the coverage and the cost into the expected reward. Considering the trustworthiness and cost may decrease the error and the cost for acquiring the necessary information (TrustEvalCost in Figure 15 and Figure 17), but this does not help satisfy the information requirements (Figure 16). Similarly, considering the trustworthiness and coverage may decrease the error and increase the coverage (TrustEvalFC in Figure 15 and Figure 17), but does not help reduce the information acquisition cost (Figure 16).

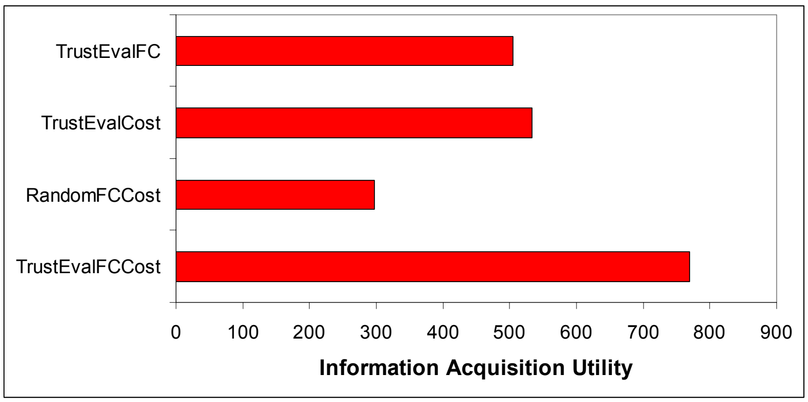

Figure 18 Information Acquisition Utility in Exp 1.1

The information acquisition utility can be maximized when an information consumer agent considers the three evaluation metrics together, as in Figure 18. In the figure, TrustEvalFCCost results in the highest information acquisition utility, even if each metric may not be maximized (coverage), or minimized (MSE, cost). Consequently, an information consumer agent can maximize the subsequent goal achievability by maximizing the information acquisition utility.

The following experiments take a closer look at the effect of trustworthiness on the information acquisition utility by considering the sets of information providers guaranteeing a full coverage and with the assumption of unit cost per information provider.

Table 4 Experiment Setups for Exp 1.2 and Exp 1.3

Parameters	Exp 1.2	Exp 1.3
Number of Providers	100	{20, 40, 80}
Number of Requirements per Consumer Agent	30	5
Number of Timesteps	500	500
Number of Runs	10	10
TRUST_BOOTSTRAP_TS	10	{1, 20 40, 60, 80, 100, 120, 140, 160}
% Providers with errors	{1, 20, 40, 60, 80, 100}	100
Error (mean, variance)	(agent id / Number of Providers, agent id / Number of Providers)	(agent id / Number of Providers, agent id / Number of Providers)
Cases	TrustKnownFCCost TrustEvalFCCost RandomFCCost	TrustEvalFCCost
Performance Measure	MSE	MSE Runtime (ms)

Table 4 shows the experiment setups for Exp 1.2 and Exp 1.3. In the experiments, a consumer agent can select an information provider per its information requirement. In the table, **Cases** represent the information consumer agent's partner selection schemes. In **TrustKnownFCEval**, an information consumer agent has access to global knowledge about the information providers' trustworthiness. In other words, the accurate error distribution of each information provider is known to each information consumer agent. Therefore, information consumer agents can select the best information providers. In **TrustEvalFCCost**, an information consumer agent evaluates the trustworthiness of the information providers based on the initial bootstrap interactions and the following interactions with selected information providers. The evaluated trustworthiness is used for selecting appropriate information providers. In **RandomFCCost**, an information consumer agent selects random information providers, which results in full coverage of information requirements. Therefore, while an information consumer agent does not take into account the quality of information, it can acquire all the required information elements. In Exp 1.2, Mean-Square-Error (**MSE**) of the acquired information is used to evaluate the performance of the algorithms. **Runtime** represents the computational burden of the consumer agent (Exp 1.3), and is measured in millisecond in the experiment.

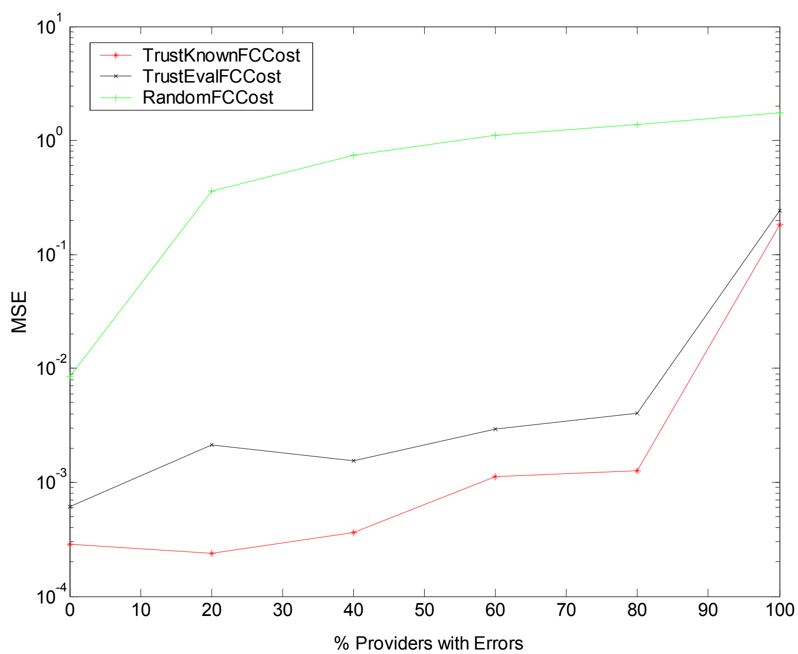

Figure 19 Mean Square Errors versus Percentage of Erroneous Information Providers (Exp 1.2)

Figure 19 shows the results of Exp 1.2. Since an information consumer agent knows which information provider agents are the best to cover all the information requirements in **TrustKnownFCCost**, **TrustKnownFCCost** results show the best "optimal" performance, and the MSE increases only as the percentage of erroneous information providers increases. When an information consumer agent does not have global knowledge about the trustworthiness of the information provider agents (which is usually the case in multi-agent systems), **TrustEvalFCCost** shows comparable results to **TrustKnownFCCost**, while random selections (**RandomFCCost**) result in higher errors. In summary, Exp 1.2 shows that the trustworthiness evaluation significantly improves the quality of received information in the presence of inaccurate information providers, thus increasing the information acquisition utility.

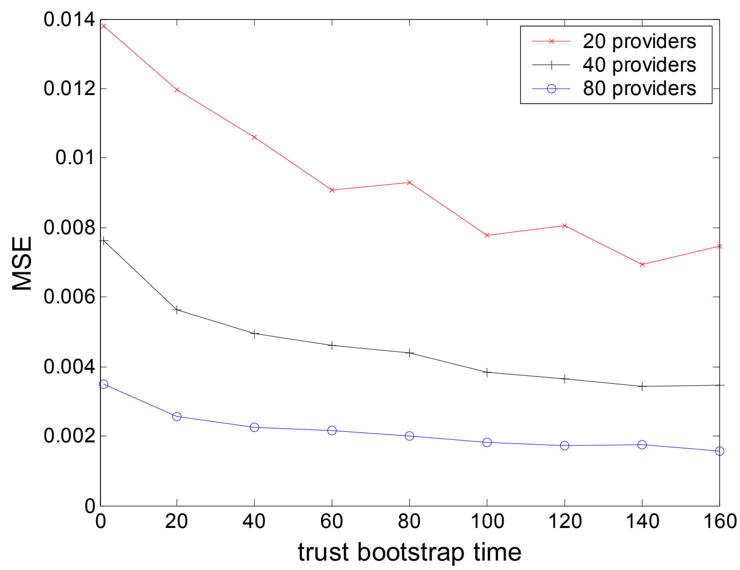

Figure 20 Mean Square Errors versus Trust Bootstrap Time (Exp 1.3)

Figure 20 shows the results from Exp 1.3. The figure shows the MSE for different quantities of information provider agents as the trust bootstrap time grows. As more time for trust bootstrap is allowed, the MSE decreases because an information consumer agent has more time to build more accurate models of trustworthiness. The MSE decreases as the number of available information providers increases, since the information consumer agent has more options for information provider selection, with higher trustworthiness as the number of information providers increases according to the experiment setup.

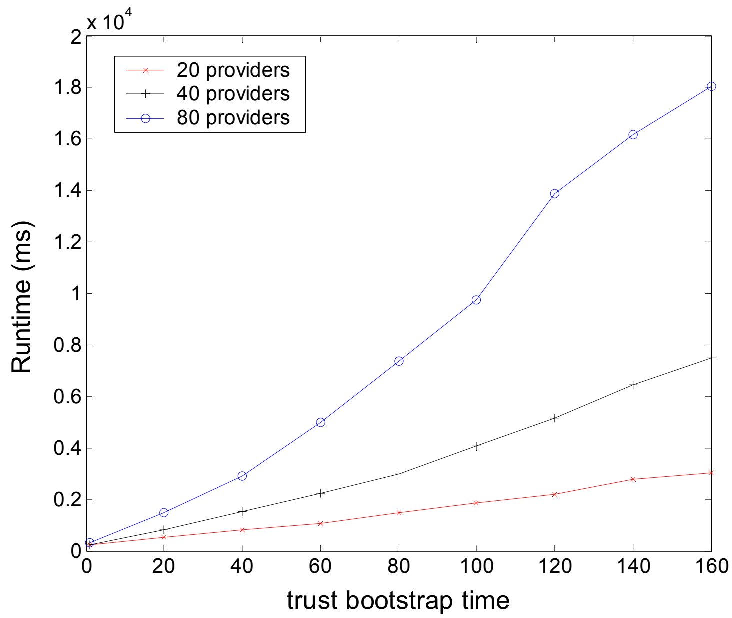

Figure 21 Runtime versus Trust Bootstrap Time (Exp 1.3)

Although allowing more time for agents to build their trust models of potential information providers (more TRUST_BOOTSTRAP_TS) results in less error in acquired information, more time for trust bootstrap results in an increase in runtime. During the TRUST_BOOTSTRAP_TS, an information consumer agent makes information requests from all available information providers and builds a trustworthiness model based on the obtained information during bootstrap time. As a result, more trust bootstrap time implies the increase of information a consumer agent has to deal with and communicate, leading to the increase of runtime as in Figure 21.

In summary, Exp 1.3 shows that more time for agents to build their trust models of potential information providers improves the quality of acquired information, while more runtime is spent for initial interactions and computations.

Table 5 Experiment Setups for Exp 1.4, Exp 1.5, Exp 1.6, and Exp 1.7

Parameters	Exp 1.4	Exp 1.5	Exp 1.6	Exp 1.7
Number of Providers	5	5	{3, 4, 5, 6}	5
Number of Requirements	3	{2, 3, 4, 5}	3	3
Number of Timesteps	128	128	128	128
Number of Runs	10	10	10	10
Num of Prov/Req	3	3	3	{2, 3, 4, 5}
Num TS/Round	{1, 2, 4, 8, 16, 32, 64}	8	8	8
Cases	HC HCSI HCCI HCRM	HC HCSI HCCI HCRM	HC HCSI HCCI HCRM	HC HCSI HCCI HCRM
Performance Measure	MSE	MSE	MSE	MSE

Table 5 presents the setup for experiments aiming to show the performance of the proposed heuristic search techniques. While the previous experiments assume a single provider selection per information requirement, multiple providers can be selected per information requirement by an information consumer for these experiments. **Num of Prov/Req** represents the number of available information providers per information requirement. In the experiments, information requests are assumed to be made in each round, and multiple timesteps can comprise a round. In every round, an information consumer agent can perform a search operation for finding the best information providers to satisfy its information requirements for the specified amount of timesteps. **Num**

TS/Round represents the number of timesteps per round, and an information consumer agent can perform its search operation for **Num TS/Round** timesteps before making information requests. **Cases** represent heuristic search techniques to be compared (**HC**: Hill-Climbing, **HCSI**: Hill-Climbing wit Source Inversion, **HCCI**: Hill-Climbing with Complementary Inversion, **HCRM**: Hill-Climbing with Random Mutation).

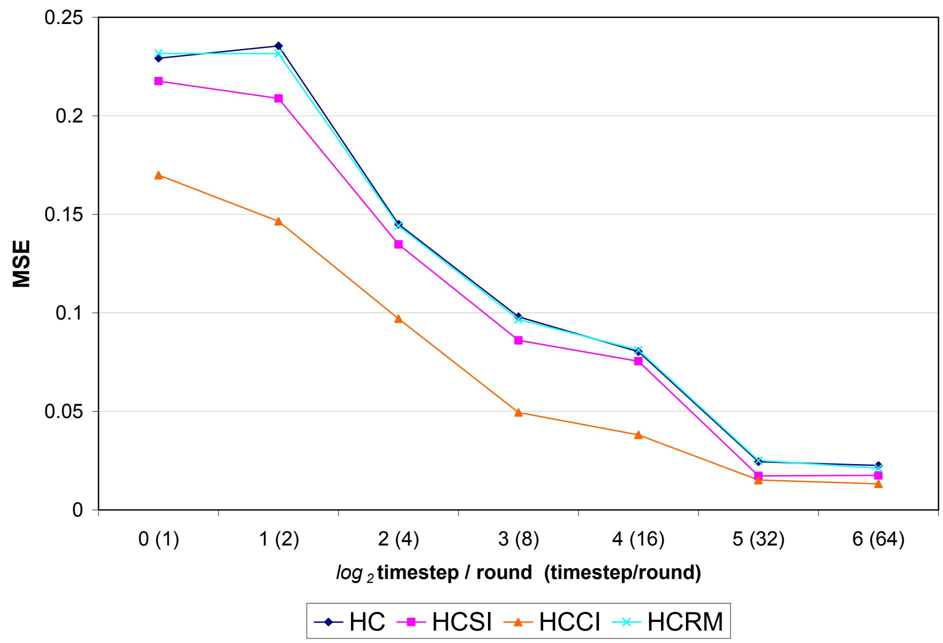

Figure 22 Mean Square Errors versus Timestep per Round (Exp 1.4)

In the results of Exp 1.4 (Figure 22), the proposed heuristic search techniques decrease the MSE of the received information as more time for the search is allocated. While HCRM does not result in the improvement of traditional HC method, HCSI and HCCI show the improvement in the quality of obtained information. Particularly, the performance of HCSI and HCCI shows more enhancement when a smaller number of timesteps constitute a round, meaning when less time is allowed for traversing search space. The results imply that the MUTATION operations help avoid the search from staying in any local optima or plateau in the search space.

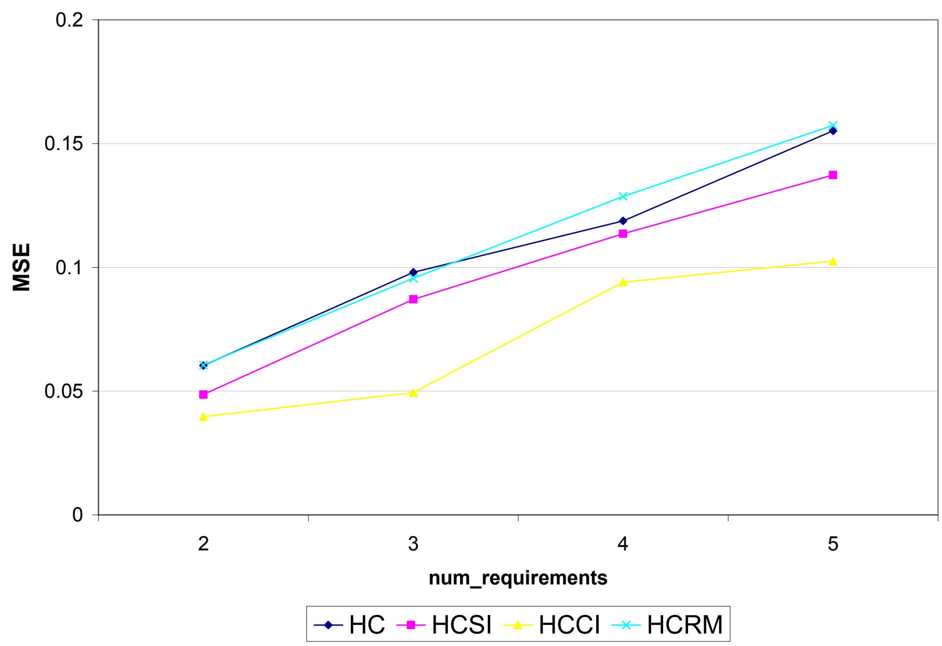

Figure 23 Mean Square Errors versus Number of Information Requirements (Exp 1.5)

Figure 23 shows the performance of the heuristic search techniques for different numbers of information requirements. The search space size increases exponentially as the number of requirements increases. For example, when the number of information requirements is 2 in Figure 23, the number of possible combinations of information providers is 49, while the number becomes 16,807 with 5 information requirements. The increase of search space size implies the increase in MSE given a fixed amount of time for the search as shown in the figure. In this experiment, HC and HCRM show similar performance in terms of MSE, while HCSI and HCCI do better in finding information providers with less error with a fixed amount of search time (**Num TS/Round**). As in the previous experiments, the results imply that the MUTATION operations help prevent the search from staying in any local optima or plateau in the search space, and accelerate the search process.

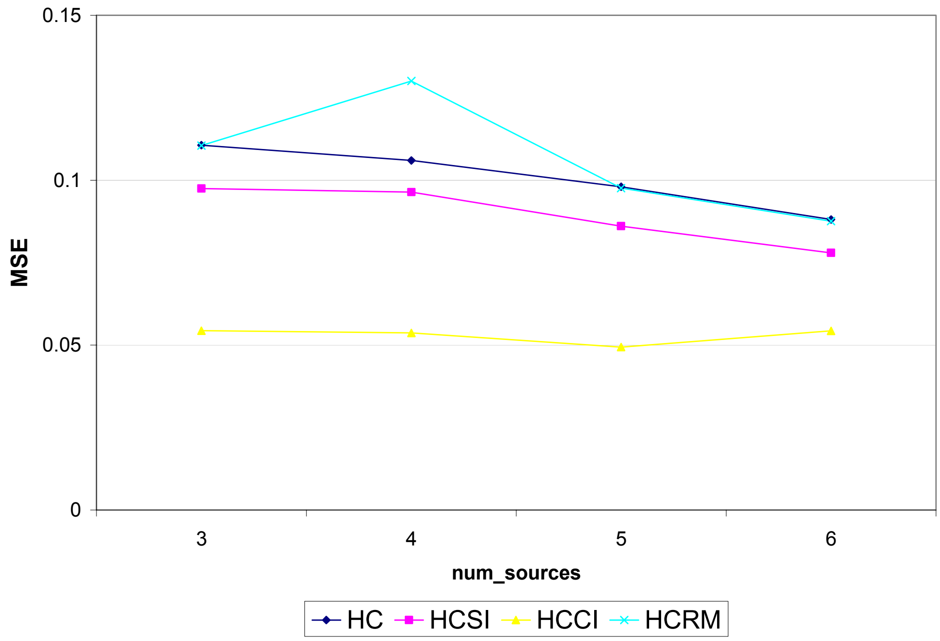

Figure 24 Mean Square Errors versus Number of Information Providers (Exp 1.6)

Figure 24 shows the result of Exp 1.6 with MSE versus the number of information providers. In this experiment, the result does not show any trends in MSE depending on the number of information providers given a fixed number of information requirements and the number of providers per information requirement. This result implies that if the provider combinations which can result in a full coverage of consumer's information requirements only are examined, the total number of providers does not affect the amount of error with fixed search time.

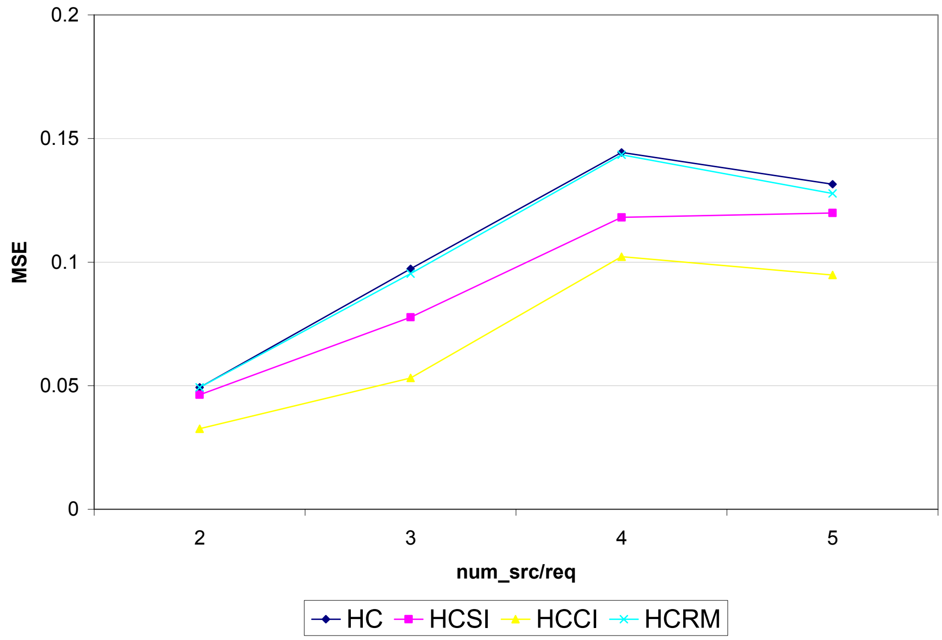

Figure 25 Mean Square Errors versus Number of Information Providers per Information Requirement (Exp 1.7)

Figure 25 shows the graph of MSE versus the number of information providers per information requirement from Exp 1.7. As the number of available information providers increases, the available options for an information consumer agent's selection of information providers increase, leading to the expansion of search space. The figure shows that HC and HCRM cannot be delineated in terms of performance, while HCSI and HCCI show the reduction of error. This result implies that the search space size is dependent on the number of providers per information requirement and the search can be improved by MUTATION operations.

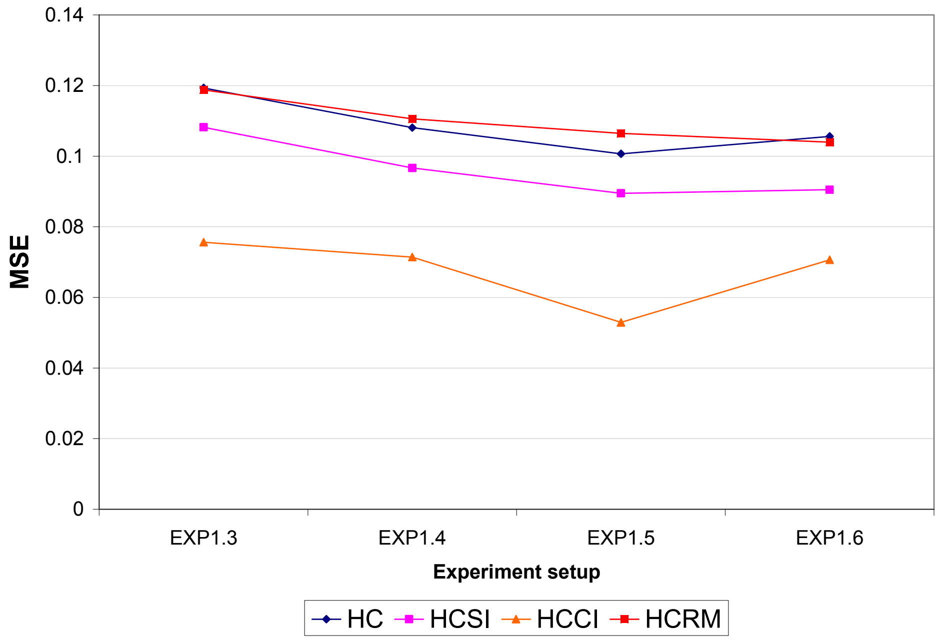

Figure 26 Average Mean Square Errors

Figure 26 presents the average mean square errors for each experiment to compare the performance of each heuristic search technique in general. HCCI shows the least amount of MSE, and HCSI shows less MSE than HC and HCRM, while HC and HCRM do not show any statistically significant difference in the performance.

In addition to the dependence of search performance on different parameters, the following observations are made from the experiment results (Exp 1.4 – Exp 1.7):

- Examining completely different combinations of information providers with hill-climbing (HCCI) helps the search quickly escape from local optima or plateau.
- Examining close neighbors with hill-climbing (HCSI) helps escape from local optima or plateau, but is not as effective as HCCI.

- Examining random nodes with hill-climbing (HCRM) does not contribute to escaping from local optima or plateau.

5.2 Collaboration among Agents

This section presents the experimental results for *CoCoAgents*' strategies as an information consumer and information provider for Research Question 2 (RQ2) in Chapter 1.

RQ2. How should an agent interact with other agents for sharing information in competitive environments?

The first set of experiments (Exp 2.1) aims to show that the proposed information sharing strategies lead *CoCoAgents* to build collaborative relationships with complementary agents. To show how the agents' requests and supply of information elements are affected by the complementary relationships, uncertainty in the quality of information is not considered in this experiment. In addition, how the emerging relationships contribute to the information acquisition is addressed.

The objective of the second set of experiments (Exp 2.2) is to justify the incorporation of the model of other agents' degree of collaboration (i.e., *ReceptionRate*) and trustworthiness into a *CoCoAgent*'s decision-making process. In this experiment, the effect of *ReceptionRate* on the efficiency of information acquisition and the effect of trustworthiness on the quality of information are investigated.

The last set of experiments (Exp 2.3) addresses the performance of *CoCoAgents* in heterogeneous environments where selfish agents reside. This experiment shows how the adaptation of the degree of collaboration contributes to *CoCoAgents'* construction of appropriate relationships with other agents. Especially, how decaying the degree of collaboration with non-interacting agents helps build appropriate collaborative relationships is investigated.

5.2.1 Experiment Setups and Results

In the experiments, each agent has a set of information requirements and a set of available information elements. The quality of available information elements offered by a respective information provider, which is not known to the other agents, is denoted by a Gaussian distribution of errors in the information. The complementary relationships between agents are divided into "*completely complementary (CC)*" and "*partially complementary (PC)*" relationships. Two agents (a_i, a_j) are completely complementary when each agent can provide all the required information of the other agent ($\mathrm{RQ}(a_i) \subset \mathrm{PR}(a_j) \wedge \mathrm{RQ}(a_j) \subset \mathrm{PR}(a_i)$) , while s partially complementary relationship is formed when each agent can provide only a subset of the other agent's required information ($\mathrm{RQ}(a_i) \cap \mathrm{PR}(a_j) \neq \varnothing \wedge \mathrm{RQ}(a_j) \cap \mathrm{PR}(a_i) \neq \varnothing \wedge \mathrm{RQ}(a_i) \not\subset \mathrm{PR}(a_j) \wedge \mathrm{RQ}(a_j) \not\subset \mathrm{PR}(a_i)$). Figure 27 shows how agents and their complementary relationships are depicted. In the figure, a set of information elements on an incoming arrow represents the information requirements (r_i, r_j) which need to be satisfied by other agents. The information elements on an outgoing arrow are a set of available information elements to other agents (r_k, r_l). Error in available information is modeled in a Gaussian distribution $N(\mu, \sigma)$ where μ is the mean value of error and σ is the variance.

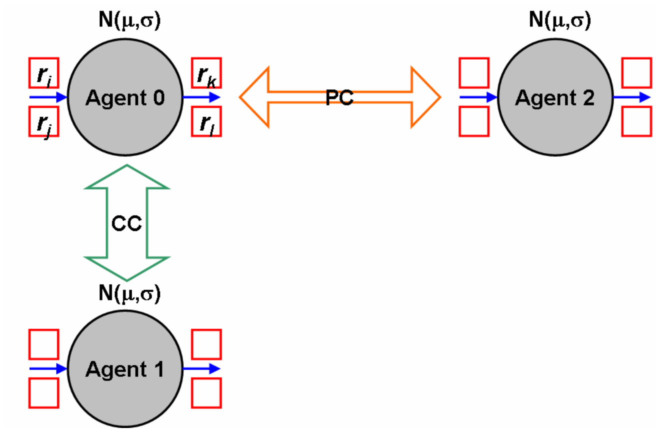

Figure 27 Visualization of Agents and Relationships

Three different configurations of agents are used to set up the complementary relationships among agents. Each configuration has sub-configurations with different allocation of available information quality. Figure 28 shows the configuration of agents where 3 agents, each with 2 information requirements and 2 available information elements, are deployed (ST1). Each agent is partially complementary with the other agents. There is only one available provider for each information requirement of each agent. All information providers in this configuration offer accurate information elements as in Table 6.

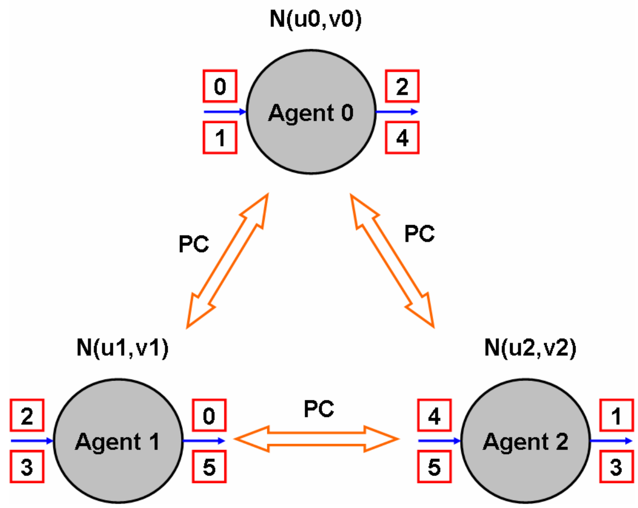

Figure 28 Configuration of Three Agents with Partial Complementary Relationships (ST1)

Table 6 Error Distribution for ST1

	(u0,v0)	(u1,v1)	(u2,v2)
ST1	(0,0)	(0,0)	(0,0)

In the second configuration (ST2) in Figure 29, 3 agents, each with 2 information requirements and 2 available information elements, are deployed. The complementary relationships are asymmetric in this configuration, such that agent 0 and agent 1 are completely complementary, while agent 2 is partially complementary with agent 0 and agent 1. In this configuration, while agent 0 and agent 1 have 2 providers for one requirement and 1 provider for another requirement, agent 2 has only 1 available provider for each information requirement. For ST2, 6 different combinations of error distributions comprise the sub-configurations as in Table 7.

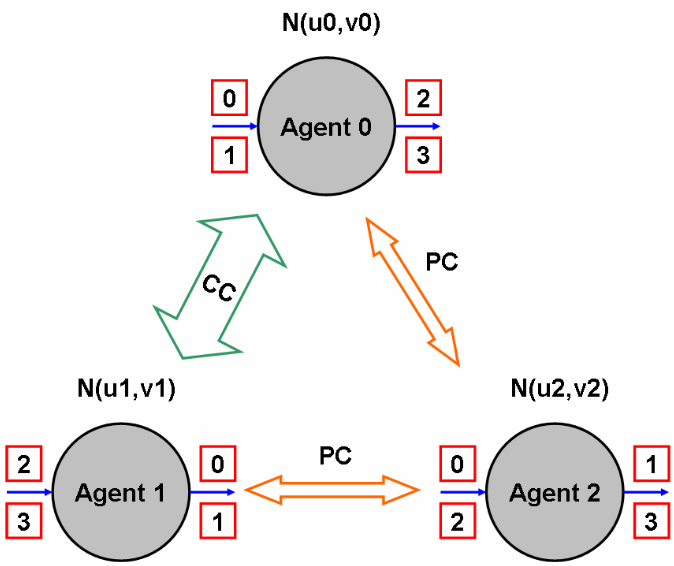

Figure 29 Configuration of Three Agents with Partial and Complete Complementary Relationships (ST2)

Table 7 Error Distributions for ST2

	(u0,v0)	(u1,v1)	(u2,v2)
ST2-1	(0,0)	(0,0)	(0,0)
ST2-2	(0,0)	(0,0)	(5,5)
ST2-3	(0,0)	(5,5)	(0,0)
ST2-4	(5,5)	(0,0)	(0,0)
ST2-5	(5,5)	(0,0)	(5,5)
ST2-6	(5,5)	(5,5)	(0,0)

To deal with more complicated cases, the third configuration of agents (ST3) in Figure 30 deploys 4 agents, each with 2 information requirements and 2 available information requirements. In the configuration, completely complementary relationships are allocated between agent 0 and agent 3, and between agent 1 and agent 2. Each agent is partially complementary with the other agents. Therefore, there are multiple providers for each information requirement. Depending on the assignments of error distributions, 8 sub-configurations are provided, as in Table 8.

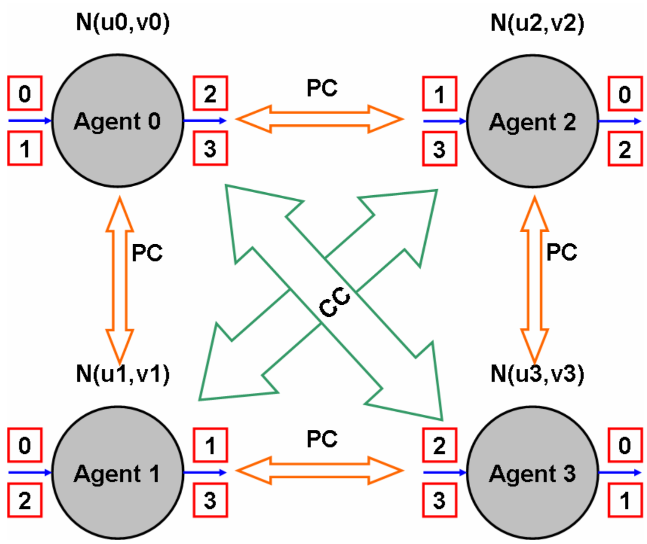

Figure 30 Configuration of Four Agents with Partial and Complete Complementary Relationships (ST3)

Table 8 Error Distributions for ST3

	(u0,v0)	(u1,v1)	(u2,v2)	(u3,v3)
ST3-1	(0,0)	(0,0)	(0,0)	(0,0)
ST3-2	(0,0)	(0,0)	(0,0)	(5,5)
ST3-3	(0,0)	(5,5)	(5,5)	(0,0)
ST3-4	(0,0)	(5,5)	(0,0)	(0,0)
ST3-5	(5,5)	(0,0)	(0,0)	(0,0)
ST3-6	(5,5)	(0,0)	(0,0)	(5,5)
ST3-7	(5,5)	(5,5)	(5,5)	(0,0)
ST3-8	(5,5)	(5,5)	(0,0)	(0,0)

With the configurations of agents with different complementary relationships and error distributions, Table 9 provides experiment setups for Exp 2.1, Exp 2.2 and Exp 2.3.

Table 9 Experiment Setups for Exp 2.1, Exp 2.2, and Exp 2.3

Parameters	**Exp 2.1**	**Exp 2.2**	**Exp 2.3**
Configuration of Agents	ST1 ST2-1 ST3-1	ST2-1 ~ ST2-6 ST3-1 ~ ST3-8	ST3-1
Participating Agents	*CoCoAgents*	*CoCoAgents*	*CoCoAgents* Selfish Agent (a_1)
Number of Timesteps	200	200	{200, 400, 600, 800, 1000}
Number of Runs	100	100	100
***DoC* incremental coeff α**	0.1	0.1	0.1
***DoC* decay rate δ**	0.99	0.99	0.99
Initial *DoC*	0.9	0.9	0.9
TRUST_BOOTSTRAP_TS	20	20	20
Cases	TR_n_RR	TR_n_RR TR RR NoTR_n_NoRR	ADoC with Decay ADoC with No Decay
Performance Measure	NumFinalStates DoC	NumFinalStates NumMsg/TS MSE	NumFinalStates NumMsg/TS DoC

In Table 9, **Configuration of Agents** determines the number of agents, the number of information requirements, the number of available information elements, the complementary relationships among agents, and the error distribution of each agent. **Participating Agent** specifies the types of the deployed agents. **Number of Timesteps** decides the maximum number of timesteps, and **Number of Runs** denotes the number of experiment runs to be used for results. ***DoC* incremental coeff α** is the incremental coefficient α which determines the amount of change in each trigger of the adaptation of the degree of collaboration as in Algorithm 4. ***DoC* decay rate** δ decides the decay speed of the degree of collaboration with non-interacting agents (i.e., agents the consumer agent does not request information from). **Initial *DoC*** is the initial value of the degree of collaboration.

TRUST_BOOTSTRAP_TS is the number of timesteps used to build the initial model of other agents' trustworthiness. **Cases** represents the algorithms used for performance comparison. TR_n_RR, TR, RR, and NoTR_n_NoRR are the variations of the proposed information request strategy as a information consumer. TR_n_RR is the default decision-making process using the proposed algorithm which considers the trustworthiness and *ReceptionRate* in estimating the expected rewards. TR and RR represent the use of trustworthiness or *ReceptionRate* exclusively in expected rewards calculation. With NoTR_n_NoRR, *CoCoAgents* do not use trustworthiness and *ReceptionRate* in expected rewards. As a result, NoTR_n_NoRR is basically a random selection.

In Exp 2.1 and Exp 2.2, the strategy as an information provider is not altered, meaning the deployed *CoCoAgents* use the proposed *adaptive degree of collaboration* (Algorithm 4 in Chapter 4) to decide the information provider strategy. ADoC with Decay and ADoC with No Decay are the variations of information providers' strategy. ADoC with No Decay does not decay the degree of collaboration with non-interacting agents (i.e., δ=1), while ADoC with Decay sets the decay rate δ to be less than 1. In Exp 2.3, *CoCoAgents*' information request strategy is controlled by the proposed algorithm with TR_n_RR. For **Performance Measure**, NumFinalStates represents the number reaching the final state from the initial state in the stochastic game representation (e.g., from A to H in Figure 11). In the final state, the information requirement is empty and the final state transfers to the initial state without any cost. Therefore, NumFinalStates represents how many times the information requirements are fully satisfied (i.e., how many times all the requirements are obtained). NumMsg/TS represents the average number of messages an agent sends out in each timestep. In each timestep, a set of requests can be made and a set of replies can be received. The messages include the information requests and replies to other agents. DoC is the degree of collaboration, and MSE is the mean square error of acquired information elements.

Figure 31, Figure 32, and Figure 33 show the final degree of collaboration from each agent's perspective in Exp 2.1.

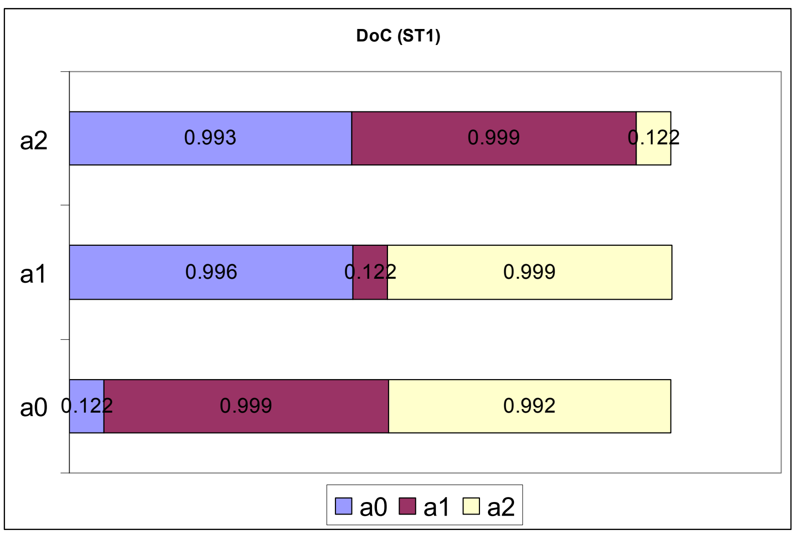

Figure 31 Final degree of collaboration in ST1

In Figure 31, each agent reciprocally reaches a high degree of collaboration with the other agents since both of the other agents are necessary to each agent in order to obtain the required information. Each agent's degree of collaboration with itself is simply decayed over time and reaches a low value as a result.

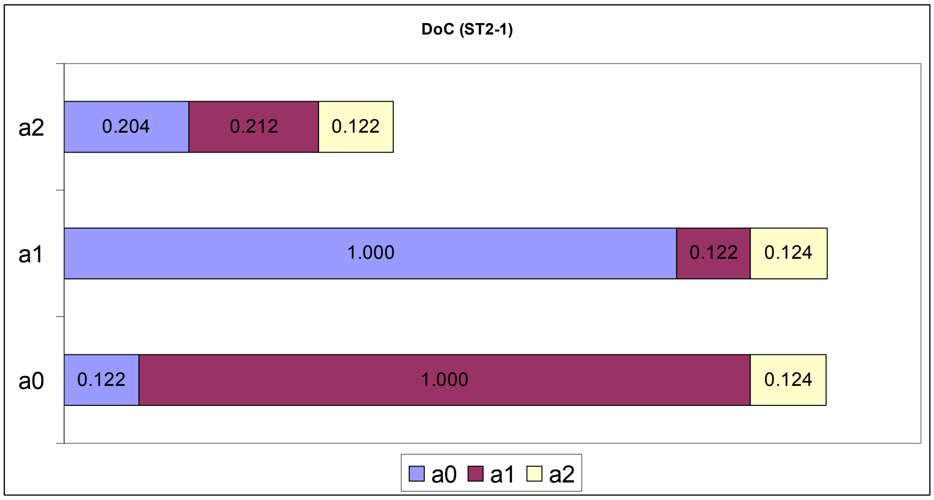

Figure 32 Final degree of collaboration in ST2-1

Figure 32 shows the final degrees of collaboration in the configuration ST2-1. Between completely complementary agents (agent 0 and agent 1), the degrees of collaboration become reciprocally high, building strong collaborative relationships while agent 0 and agent 1 have a low degree of collaboration with agent 2 which is partially complementary. In the initial stage of interactions, agent 0 can request information from agent 1 and agent 2. However, since agent 1 is completely complementary with agent 0, more requests and replies are exchanged between agent 0 and agent 1. As a result, the degree of collaboration between agent 0 and agent 1 converges to a high value faster than the degree of collaboration between agent 0 and agent 2, leading to a strong collaborative relationship between completely complementary agents.

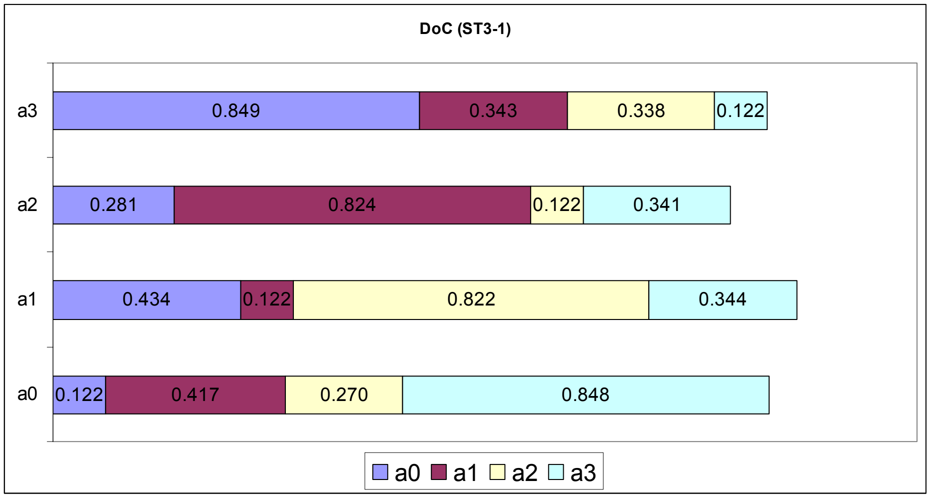

Figure 33 Final degree of collaboration in ST3-1

Figure 33 shows the final degrees of collaboration in the configuration ST3-1. It is observed that high degrees of collaboration result between completely complementary agents (agent 0–agent 3, agent 1–agent 2). While each agent mostly interacts with completely complementary agents, each agent's degrees of collaboration with partially complementary agents are not minimal, as opposed to ST2-1 (i.e., agent 0 and agent 1 still maintain weak collaborative relationships). In ST2-1, agent 0 must request information for one of its two information requirements from agent 1, but in ST3-1 each agent is not completely dependent on completely complementary agents. An agent can fully satisfy the information requirements even from partially complementary agents. Therefore, there is still a small amount of interactions between partially complementary agents, in the cases where an agent fails to receive information from the selected information providers.

While the degree of collaboration represents the collaborative relationships between agents, the number of final states covered within a given timestep

(NumFinalStates) represents how efficiently each agent gets information requests satisfied.

In summary, Exp2.1 shows that the information sharing strategies lead agents to build collaborative relationships with complementary agents.

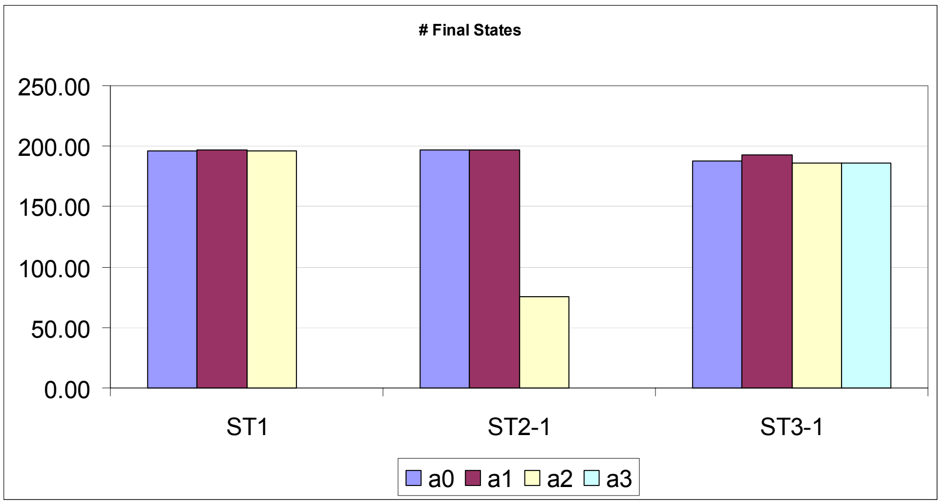

Figure 34 Number of Final States Covered after 200 Timesteps (ST1, ST2-1, ST3-1)

Figure 34 shows the number of final states covered after 200 timesteps. Ideally, if an agent can obtain all the required information at each timestep, the maximum number of final states equals to the maximum number of timesteps in the experiment (which is 200 in this case). In the figure, each agent in ST1 achieves the number of final states close to 200. In ST2-1, the number of final states for agent 0 and agent 1 reaches close to 200, while agent 2 achieves around 75. In ST3-1, all agents achieve a high number of final states, which is close to 200. From all the results, it is observed that *CoCoAgents* tend to build collaborative relationships with completely complementary agents and achieve the satisfaction of information requests repeatedly.

In the following experiment results (Exp 2.2), the effect of *ReceptionRate* on the efficiency of information request strategy and the effect of trustworthiness evaluation on the quality of information are investigated. Figure 35 to Figure 40 are the results from agent 0's perspective.

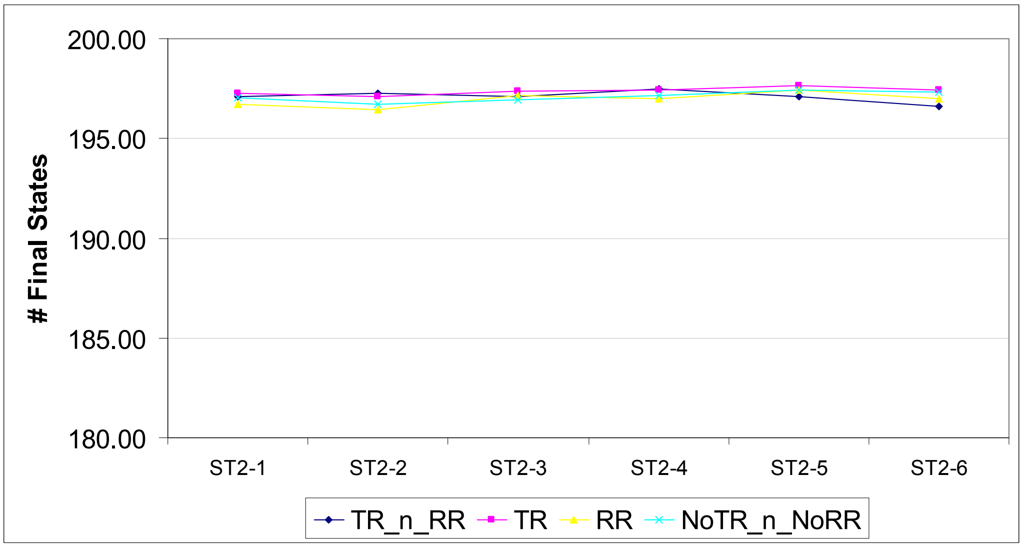

Figure 35 Number of Final States Covered after 200 Timesteps versus Agent Configuration (ST2)

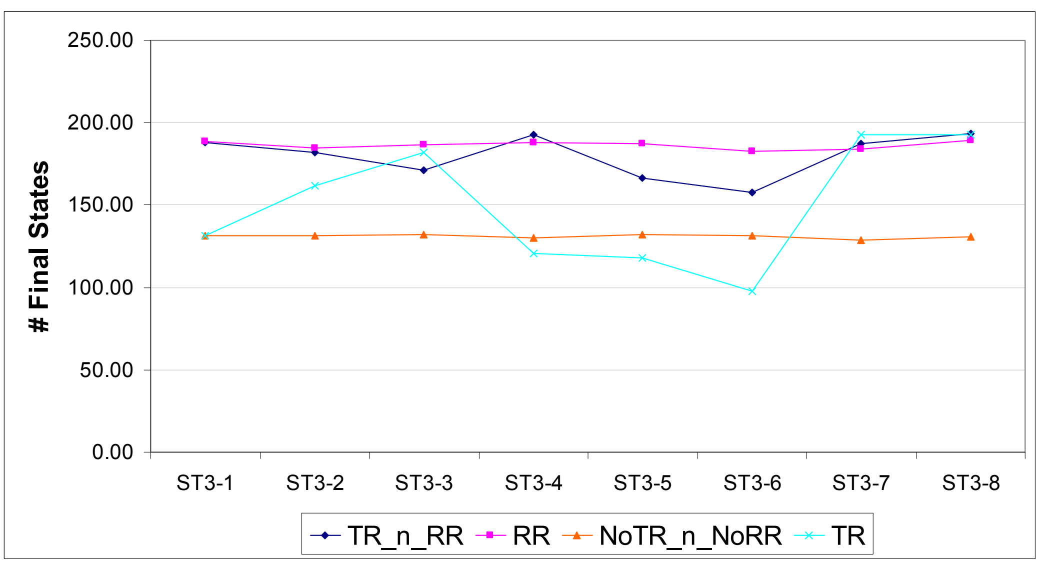

Figure 36 Number of Final States Covered after 200 Timesteps versus Agent Configuration (ST3)

Figure 35 and Figure 36 show the number of final states covered after 200 timesteps for different configurations of agents and different variations of information request strategy. In Figure 35 (ST2), the number of final states is not affected by the information request strategy because the relationships are dominated by complementary relationships. On the other hand, depending on the evaluation metrics considered for information request strategy in ST3 (TR_n_RR, TR, RR, NoTR_n_NoRR), the efficiency of information acquisition changes as in Figure 36. The effect of *ReceptionRate* on the efficiency of information request can be discovered by comparing NoTR_n_NoRR with RR. By incorporating *ReceptionRate* (RR) in expected rewards calculation, *CoCoAgents* can achieve a higher number of final states than NoTR_n_NoRR.

The number of final state using TR fluctuates without any trends because information providers who can provide a high quality of information are selected without considering whether they are willing to provide or not (TR in Figure 36). If *ReceptionRate* and trustworthiness are incorporated into expected rewards calculation together (TR_n_RR), the number of final states stays near RR but shows deviations in some cases because TR_n_RR pursues the maximization of expected rewards with combined metrics of trustworthiness, coverage, and cost along with RR. In summary, incorporating RR into the expected reward helps agents make requests to more collaborative agents. Therefore, agents can achieve more efficient information acquisition.

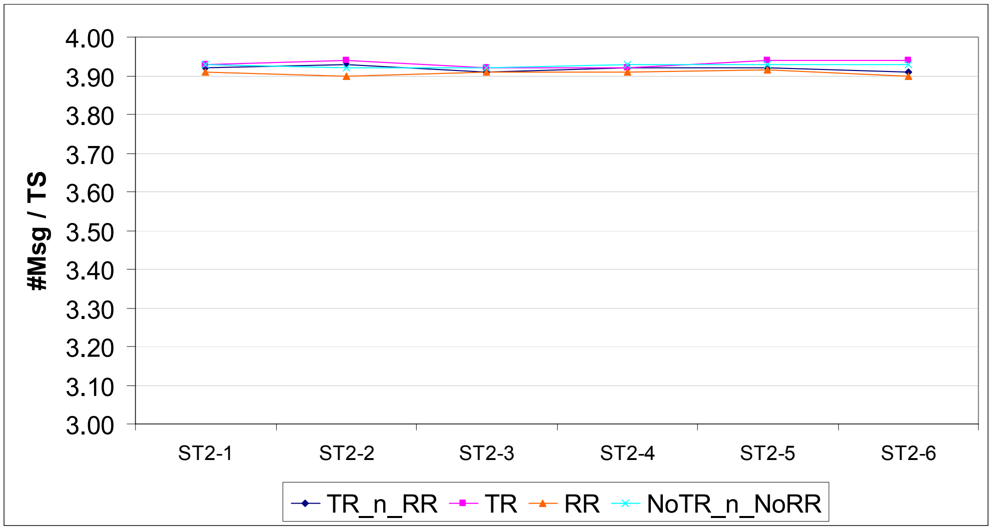

Figure 37 Number of Messages per Timestep versus Agent Configuration (ST2)

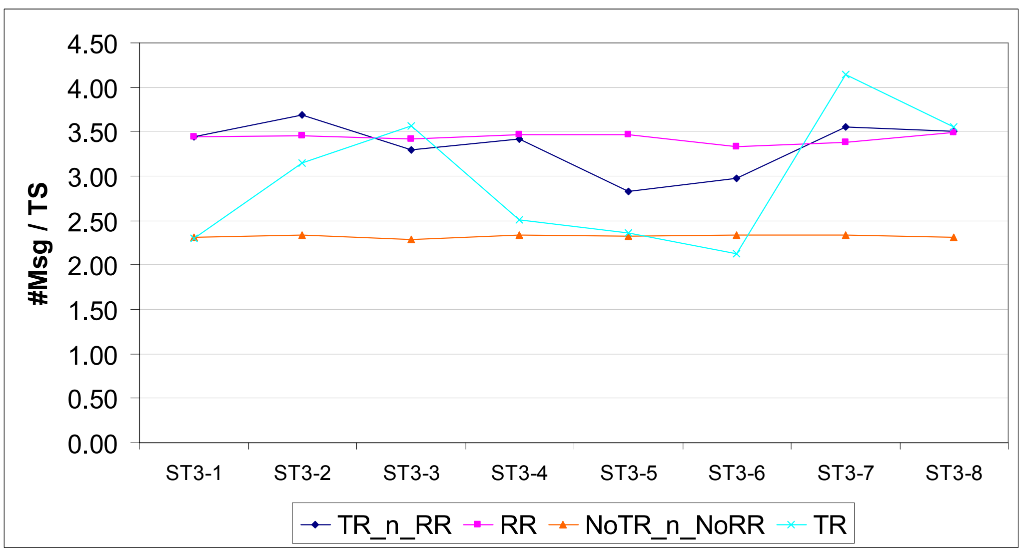

Figure 38 Number of Messages per Timestep versus Agent Configuration for (ST3)

Similarly, the number of message per timestep is affected by *ReceptionRate* modeling. In Figure 37, the number of messages per timestep is not affected by information request strategies because the request strategy is dominated by complementary relationships and the same information provider strategy is used for each case. Figure 38 shows similar patterns with that of Figure 36. If an agent does not consider *ReceptionRate* and trustworthiness (NoTR_n_NoRR), the agent may need to request the same set of information repeatedly without receiving responses, so the number of messages per timestep is low. On the other hand, if *ReceptionRate* is considered (RR), an agent requests information from the agents which seem to be the most willing to provide information, leading to higher number of messages per timestep to deal with. In summary, a strong collaborative relationship encourages active interactions between agents. Higher NumMsg/TS represents more reciprocal information exchanges.

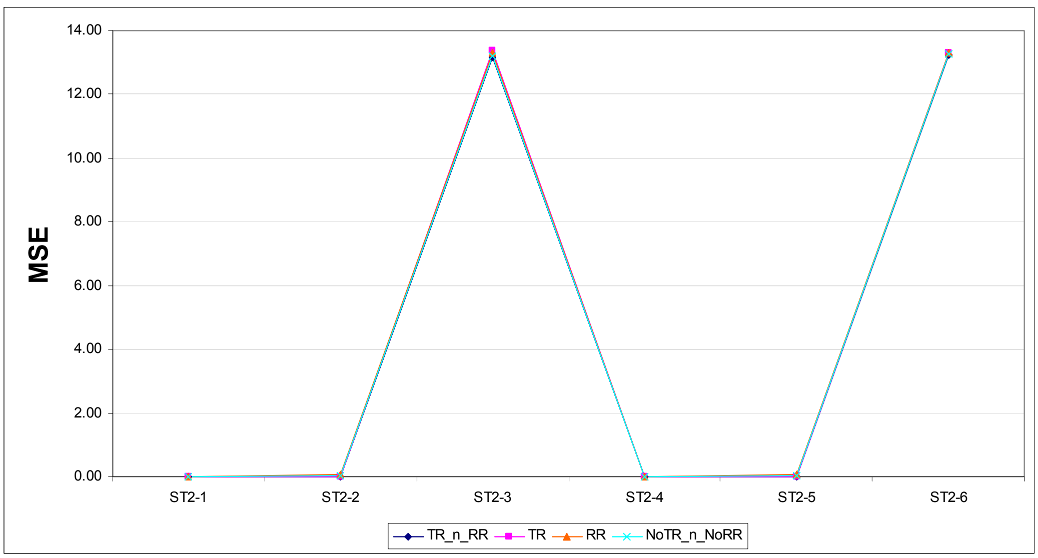

Figure 39 Mean Square Errors versus Agent Configuration (ST2)

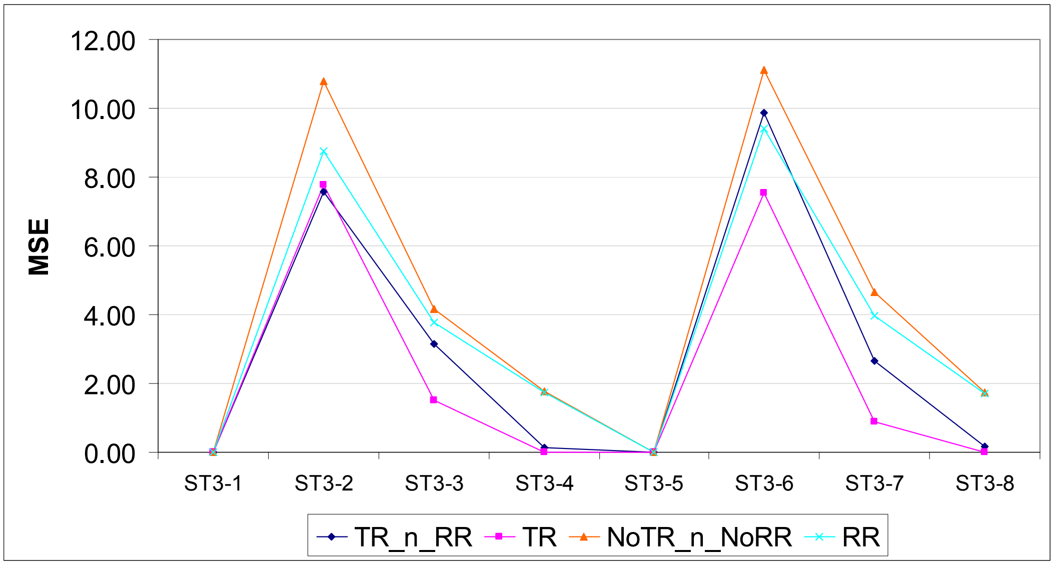

Figure 40 Mean Square Errors versus Agent Configuration (ST3)

Figure 39 and Figure 40 show the mean square errors (MSE) of the obtained information for different configurations of agents and different information request strategies. Similar to Figure 35 and Figure 37, MSE in ST2 (Figure 39) is not affected by the metrics for information request strategy decision. On the other hand, MSE without considering trustworthiness and *ReceptionRate* (NoTR_n_NoRR) is higher than the case where trustworthiness is considered for information request strategy (TR), as in Figure 40. In summary, incorporating TR into expected reward helps agents select the information providers providing more accurate information elements.

In the following experiment results (Exp 2.3), how *CoCoAgents* perform in the presence of a selfish agent is investigated.

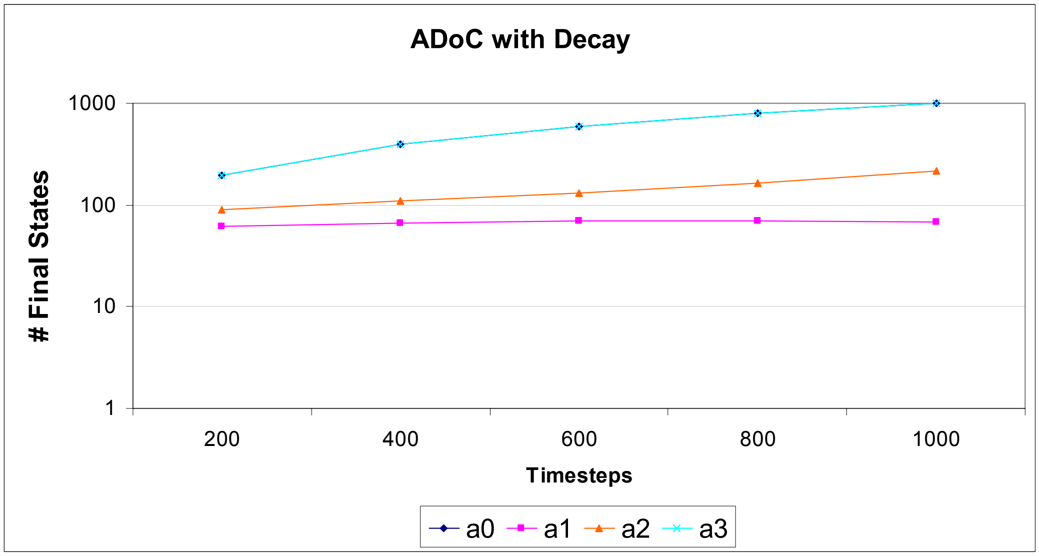

Figure 41 Number of Final States Covered versus Maximum Timesteps (Adaptive DoC with Decay)

Figure 41 shows the number of final states reached by each agent when an agent (agent 1) is selfish in a log scale graph. *CoCoAgents* (agent 0, agent 2, and agent 3) are equipped with the proposed strategies for an information consumer and information provider. Since agent 0 and agent 1 are completely complementary, they build a strong collaborative relationship and achieve active interactions satisfying each other's deficit. Agent 2 does not have a completely complementary agent because agent 2 cannot receive any information from agent 1. Therefore, agent 2 tries to build a collaborative relationship with agent 0 and agent 3. However, since there is already a strong collaborative relationship between agent 0 and agent 3, agent 2 can be involved in fewer interactions by building weak collaborative relationships with agent 0 and agent 3. On the other hand, agent 1 is isolated from the interactions. Once *CoCoAgents* realize that an agent is selfish, they tend not to request information from the selfish agent and decay the degree of collaboration with the non-interacting agent. As a result, a selfish agent is eventually isolated from the other agents. In Figure 41, agent 1's number of final states stays constant near 60 although the maximum number of timesteps increases from 200 to 1000, because agent 1 is isolated.

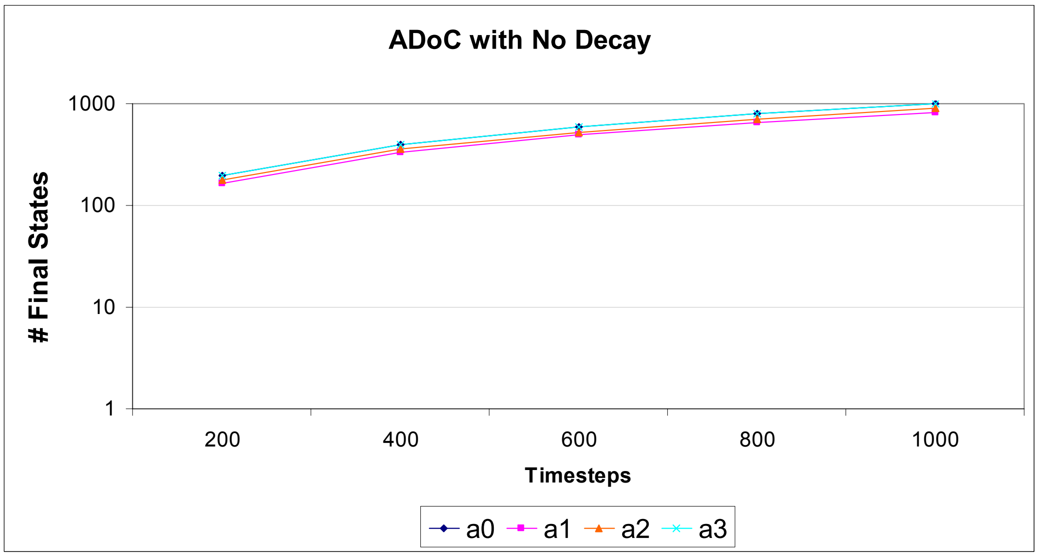

Figure 42 Number of Final States Covered versus Maximum Timesteps (Adaptive DoC with No Decay)

If a *CoCoAgent* does not decay the degree of collaboration with non-interacting agents (Figure 42), the *CoCoAgent* is vulnerable to exploitation from other agents. From the figure, all agents equivalently achieve high number of final states even though agent 1 is selfish. Vulnerability to exploitation is identifiable from Figure 43 and Figure 44.

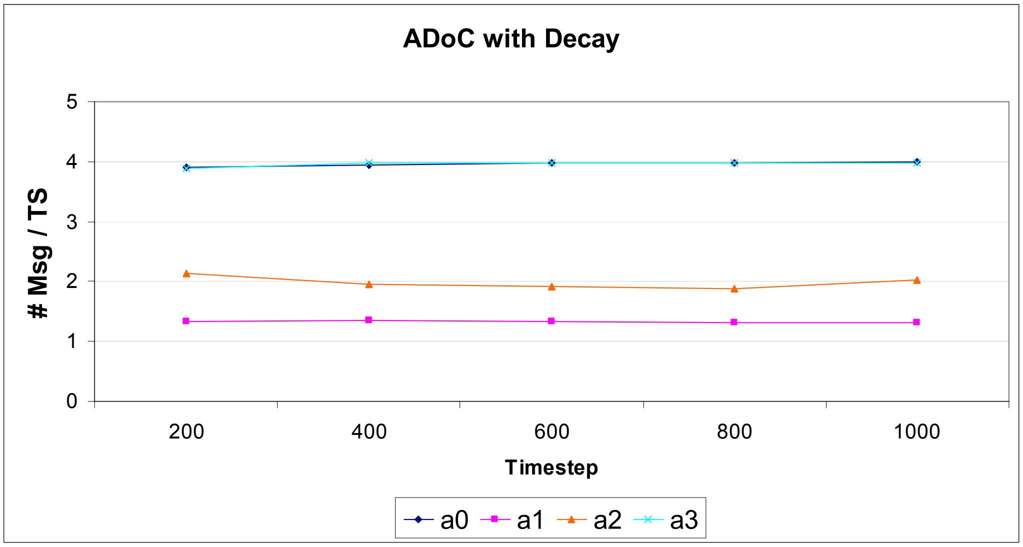

Figure 43 Number of Messages per Timestep versus Maximum Timesteps (Adaptive DoC with Decay)

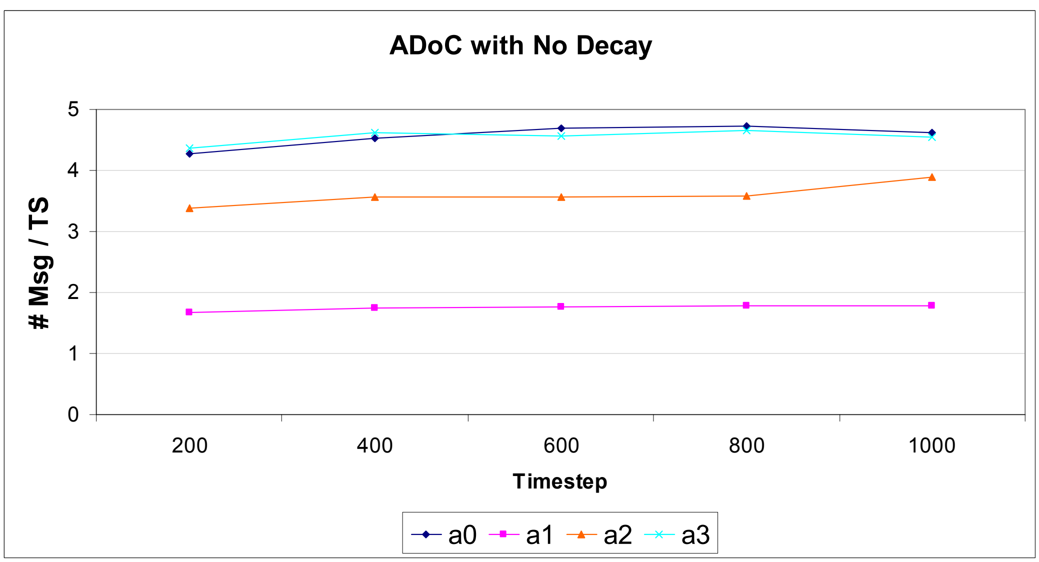

Figure 44 Number of Messages per Timestep versus Maximum Timesteps (Adaptive DoC with No Decay)

Figure 43 shows the number of messages per timestep when the degree of collaboration with non-interacting agents is decayed over time. On the other hand, the degree of collaboration with non-interacting agents is not decayed in Figure 44. In Figure 43, the number of messages per timestep of agent 0 and agent 3 stays near 4 (2 information requests and 2 information supply) because they form a strong collaborative relationship. However, in Figure 44, agent 0 and agent 3's numbers of messages per timestep are higher than agent 0 and agent 3's numbers of messages per timestep for decaying the degree of collaboration with non-interacting agents as in Figure 43, meaning that agent 0 and agent 3 provide more information to other agents. Agent 2's number of messages per timestep also increases if decaying the degree of collaboration is not deployed. This situation can be interpreted that a selfish agent (agent 1) is acquiring information without any contribution to other agents. Figure 45 and Figure 46 provide evidence for this phenomenon. Figure 45 shows the degree of collaboration when *CoCoAgents* decay the degree of collaboration with non-interacting agents, and Figure 46 shows the degree of collaboration when the decaying scheme is not deployed. From the figures, if a decaying scheme is not deployed, agents are open to requests from selfish agents by keeping a high degree of collaboration with non-interacting agents.

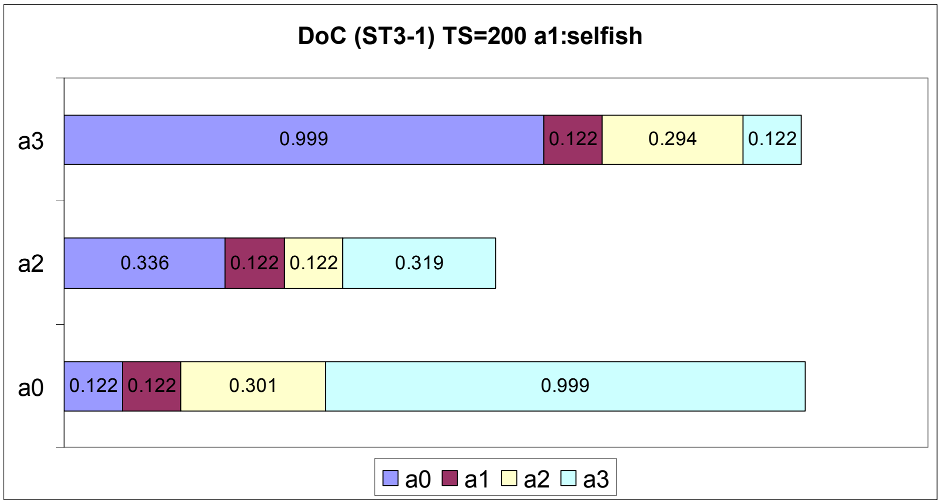

Figure 45 Final Degree of Collaboration using Adaptive DoC with Decay in the presence of Selfish Agent

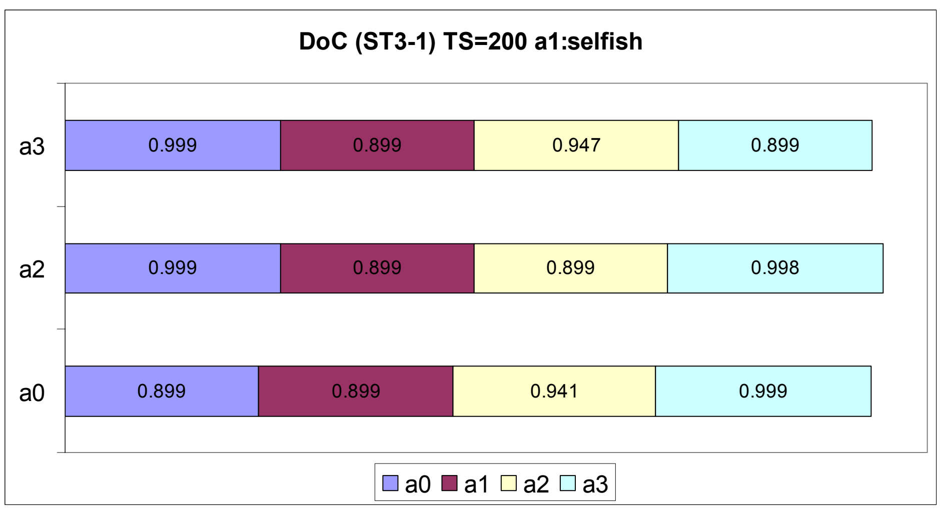

Figure 46 Final Degree of Collaboration using Adaptive DoC with No Decay in the presence of Selfish Agent

5.3 SUMMARY

In this chapter, the experimental results are presented to answer the research questions in partner selection schemes and collaboration strategies among agents. The answers to the questions can be summarized as follows:

In partner selection,

- Information acquisition utility can be maximized by considering the coverage, cost and trustworthiness together.
- Information quality can be increased by evaluating the trustworthiness of information providers and incorporating the evaluation into the selection criteria.
- Information quality can be increased by allowing more bootstrapping time for building initial trustworthiness, while more bootstrapping time implies more computation time.
- The proposed heuristic search techniques (HCSI: Hill-Climbing with Source Inversion, HCCI: Hill-Climbing with Complementary Inversion) aids agents in finding the combination of information providers who contribute more to the information acquisition utility by escaping from local optima or plateau in search operations.

In collaboration strategies among agents,

- *CoCoAgents* with proposed information sharing strategies tend to build strong collaborative relationships with completely complementary agents, and strong collaborative relationships help the efficient acquisition of required information.

- *CoCoAgents* can increase the efficiency of information requests, thus achieve the information acquisition more effectively by incorporating the models of other agents' degree of collaboration into the expected rewards.
- *CoCoAgents* can increase the quality of the acquired information by incorporating the trustworthiness evaluations of other agents into the expected rewards.
- If a decaying scheme is not deployed, agents are open to requests from selfish agents by keeping a high degree of collaboration with non-interacting agents.
- An adaptive degree of collaboration helps in building appropriate relationships with other agents and decaying the degree of collaboration with non-interacting agents contributes to exploitation avoidance.

CHAPTER 6

CONCLUSION

This dissertation presents information sharing strategies to maximize information acquisition utility and validate the following hypothesis:

The information sharing strategies enable agents to obtain required information of high quality by building collaborative relationships with complementary and trustworthy agents.

This chapter revisits the research questions and discusses the contributions of this research.

6.1 REVISITING RESEARCH QUESTION 1

> *"How do information consumer agents select the most appropriate information providers so that information acquisition utility can be maximized?"*

The first research question addresses the problem of partner selection. In partner selection, information providers always provide the requested information to the information requesters. However, the quality of information can vary from different information providers. The objective of the proposed partner selection scheme is to select the appropriate set of information providers who maximize the information acquisition utility. Information acquisition utility is defined in terms of coverage, trustworthiness, and cost. Given a set of information providers for information requirements, the coverage offered by respective information providers represents the percentage of information requirements the respective provider can satisfy. Trustworthiness represents the accuracy and consistency of the information providers, modeled by the error distribution of the information provider using statistical methods. The cost of information acquisition can occur from various sources. The number of messages for information acquisition is used to represent the cost in this dissertation.

When the objective of information consumer is to select a single information provider per information request, finding the optimal solution based on those evaluation metrics is tractable for a set of information requirements. However, if multiple information providers per information requirement can be selected, the computation complexity of finding the optimal solution increases exponentially as the number of available information providers and the number of requirements increases. The heuristic search techniques for finding the near-optimal solution given a limited amount of search time are presented. The proposed heuristic search techniques adopt the hill-climbing algorithm and genetic algorithm.

The findings from the experimental results show the properties of the proposed algorithms as follows. Information acquisition utility can be maximized by considering the coverage, cost and trustworthiness together (Exp 1.1). If necessary information should be secured for goal achievement, the maximization of the information acquisition utility helps identify trustworthy information providers (Exp 1.2). The initial trust model significantly impacts on subsequent partner selection. An information consumer agent can build more accurate model of trustworthiness by gathering more evidence about the quality of the information. However, the tradeoff between the accuracy of the initial trustworthiness model and the amount of computation required for building the model needs to be considered by the system designer (Exp 1.3). The proposed heuristic search techniques (HCCI: Hill-Climbing with Complementary Inversion, HCSI: Hill-Climbing with Source Inversion) using the measures of the information acquisition utility speed up finding more accurate information providers (Exp 1.4–Exp 1.7) given a limited amount of resources for computation. Using the characteristics of the search space, examining completely different combinations of information providers while performing a hill-climbing search helps to escape from local optima or plateau (Exp 1.4-Exp 1.7).

The uniqueness of this research starts from the definition of the goal-oriented information acquisition utility and partner selection from an individual agent's perspective. By incorporating goal achievability into the information acquisition utility, agents can gather the required information proactively towards the goal achievement. Also, the goal-oriented information acquisition utility does not necessitate any additional payment or incentive systems, which are often required in other approaches (e.g., [Ioannidis, Ioannidis *et al.* 2002; Yu and Singh 2003b]) . An agent's local decision using the evaluation of other agents allows the flexibility of selecting new partners in the presence of environmental dynamics. Moreover, HCCI (Hill-Climbing with Complementary Inversion) and HCSI (Hill-Climbing with Source Inversion) speed up the search by escaping the local optima or plateau quickly, and lead a consumer agent to "good-enough" partner selection swiftly with a limited amount of resources. The fast convergence to the "good-enough" partners also improves the information acquisition utility in dynamic environments.

6.2 Revisiting Research Question 2

> *"How should an agent interact with other agents for sharing information?"*

The second research question addresses the problem of agents' interactions, which can lead to the collaboration among agents in information sharing networks. In this research question, self-interested agents can act as an information consumer and information provider at the same time. The objective of each agent is to maximize the information acquisition utility by constructing appropriate relationships with other agents. Agents equipped with information sharing strategies are called *CoCoAgents* (*Competitive Collaborating Agents*). The information sharing strategies for *CoCoAgents* consist of two types. The first strategy is for the information consumer's role. The strategy for an information consumer decides from which information providers to request which information requirements. In order to take into account the previous interaction history and expected rewards in the future, stochastic games are deployed to represent the decision-making process. In the stochastic game models, the request strategy which maximizes the expected rewards is selected based on the actions of the information consumer agent and potential information provider agents. Expected rewards are calculated using the model of other agents' degree of collaboration, the trustworthiness of the other agents, and the cost of information acquisition.

The strategy for an information provider determines the degree of collaboration with other agents. The degree of collaboration is adapted using the model of other agents' degree of collaboration, which can be built based on the observations of interactions with other agents. The *adaptive degree of collaboration* is a variation of Tit-For-Tat strategy from the Iterative Prisoner's Dilemma problem [Axlerod 1984]. The action space for Tit-For-Tat is discrete (*cooperate*, *defect*) while the adaptive degree of collaboration considers continuous action space. Also, the adaptive degree of collaboration deals with the case where two agents do not make decisions simultaneously. The adaptive degree of collaboration starts from a high degree of collaboration with others. If an agent detects a decrease in other agents' degree of collaboration, the agent decreases the degree of collaboration with those agents. If an agent detects an increase in other agents' degrees of collaboration, the agent increases the degree of collaboration with those agents. If an agent decides not to request information from particular agents (called non-interacting agents), the degree of collaboration with those non-interacting agents is decayed over time. The decay of the degree of collaboration with non-interacting agents aids in avoiding exploitation in the presence of selfish agents.

The findings from the experimental results show the properties of the proposed algorithms as follows. An information request strategy enables agents to make information request decisions which lead to the acquisition of quality information from complementary and collaborative agents (Exp 2.1, Exp 2.2). Also, the adaptive degree of collaboration enables agents to encourage a more collaborative attitude toward collaborative agents. Moreover, decaying the degree of collaboration helps avoid potential exploitation by selfish agents (Exp 2.1, Exp 2.3). Finally, the information request and supply strategy triggered by the observed model of other agents contribute together to the bidirectional construction of the collaborative relationships (Exp 2.1, Exp 2.2, Exp 2.3).

The uniqueness of this research starts from the representation of the agents' information sharing in stochastic games. The stochastic game model allows the incorporation of the other agents' actions and the dynamic changes of the information requirements. Thus, an information consumer agent can find the best-responses to other information providers' actions given the model of other agents' expected actions. Also, the goal-oriented information acquisition utility, along with the information sharing strategies, provides a mechanism that encourages the emergence of collaborative relationships between complementary and trustworthy agents. Moreover, by providing the strategies for information providers and information consumers respectively, the proposed information sharing strategy can deal with the asynchronous information exchange. As opposed to the explicit agreement-based collaboration schemes (e.g., [Shehory and Klaus 1995; Sandholm, Larson et al. 1998]), the emergent nature of the collaborative relationships allows the flexibility of constructing new relationships easily in the presence of any environmental dynamics.

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